The Assessment of Spontaneous Emotional Expressions from the Frontal and Profile Facial Orientations

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Submitted in partial fulfilment of the requirements for the Degree of Doctor of Philosophy (Science) at the University of Technology Sydney.

I. Declaration

I declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy (Science) in the School of Life Sciences at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. This document has not been submitted for qualifications at any other academic institution.

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III. Publications and Presentations

Book Chapter

1. Sidavong, L., Lal, S. and Sztynda, T. (2019) Spontaneous Facial Expression Analysis Using Optical Flow Technique. In S. Mukhopadhyay, K. Jayasundera and O. Postolache (Eds.), *Modern Sensing Technologies. Smart Sensors, Measurement and Instrumentation* (Vol 29. pp. 83-101). Cham, Switzerland: Springer. https://doi.org/10.1007/978-3-319-99540-3_6

Conference presentations

2. Sidavong, L., Kilincer, S., Chow, D. K. F., Lal, S. and Sztynda, S. (2015), 'Assessment of Facial Expressions of Emotion Using Optical Flow Analysis' [poster], The combined health science conference - New Horizons 2015, Sydney, 23-25 November

3. Sidavong, L., Lal, S. and Sztynda, S. (2016), 'Asymmetries in emotional facial expressions using Optical Flow' [oral presentation], The Inter-University Neuroscience and Mental Health Conference, Sydney, 20-21 September

4. Sidavong, L., Lal, S. and Sztynda, S. (2017) 'Spontaneous facial expression analysis using optical flow' [oral presentation], The 11th International Conference on Sensing Technology (ICST *2017*), Macquarie University, Sydney, 4-6 December

Conference Proceedings

5. Sidavong, L., Lal S. and Sztynda, T. (2017). Spontaneous facial expression analysis using optical flow. *2017 Eleventh International Conference on Sensing Technology (ICST)*, 1–6. https://doi.org/10.1109/ICSensT.2017.8304482

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VII. Abbreviations

ABS	Australian Bureau of Statistics
ANS	Autonomic Nervous System
ASB	Anti-Social Behaviour
AIC	Australian Institute of Criminology
ANOVA	Analysis of Variance
AU	Action Unit
BP	Blood Pressure
CCTV	Closed Circuit Television
CK+	Cohn-Kanade
EDA	Electro Dermal Activity
EI	Emotion Intelligence
FACS	Facial Action Coding System
FE	Facial Expression
FER	Facial Expression Recognition
GSR	Galvanic Skin Response
HD	High Definition
HR	Heart Rate
HREC	Human Research and Ethics Committee
JACFEE	Japanese and Caucasian Facial Expressions of Emotion

LAQ	Lifestyle Appraisal Questionnaire
LBP	Local Binary Pattern
LDA	Linear Discriminant Analysis
LK	Lucas-Kanade
MATLAB	Matrice Laboratory
MmHg	Millimetre of Mercury
MMI	Man-Machine Interaction
PCA	Principal Component Analysis
rmANOVA	Repeated Measures Analysis of Variance
SD	Standard Deviation
SC	Skin Conductance
SCL	Skin Conductance Level
SCR	Skin Conductance Response
SMPTE	Society of Motion Picture and Television Engineers
SVM	Support Vector Machine
µS	Microsiemens
UTS	University of Technology Sydney

VIII. Abstract

The present study attempted to induce spontaneous emotions in individuals to determine whether specific pattern changes in facial movement could be determined from the frontal and profile views. A total of 142 volunteers (males = 50, and females = 92) aged between 18 to 34 years were presented with a series of short videos to induce one of three emotions: amusement, sadness, and fear. Their facial behaviours were recorded from three different facial positions (left, right, and frontal views) along with their physiological skin conductance response. After the viewing of each short film, each subject completed a self-report questionnaire to indicate what emotions they felt during certain scenes of the film.

Self-reports revealed that discrete emotions of amusement and sadness were experienced in 79.58% and 83.8% of participants compared to discrete fear which was elicited in only 50% of participants. Skin conductance responses from electrodermal activity (EDA) readings were observed during the expressions of amusement and fear whilst a mixed response pattern was seen for sadness. These skin conductance responses to sadness were marked by a reduction in tonic EDA, seen as either the presence or absence of skin conductance. As such, it was relatively difficult (particularly for sadness) to precisely reflect emotional changes by using a single physiological signal.

When it came to the behavioural level of expression, subjects displayed a variety of action units (AUs) that produced similar appearance changes that were uniquely associated with an emotion. The Lucas-Kanade optical flow and facial landmark feature extraction techniques were implemented to quantify the facial changes that occurred between onset (baseline) and peak of emotional expression. Classification using feature vectors indicated that landmark extraction method outperformed optical flow analysis achieving predictive accuracy recognitions of 71-75%, 70-72% and 70-71% compared to 49-64%, 60-68% and 64-68% in optical flow for the frontal, profile left and right facial views, respectively. Where amusement was consistently classified across all views, sadness and fear were classified best from the left and right profile views, respectively.

Thus, spontaneous emotional facial expressions are uniquely expressed and shows discrimination potential from the frontal, profile left and right facial views. This research

indicates relevance for real world applications such as in security surveillance to enhance detection of signs of emotion, associated with behaviours intent in causing harm. In particular where facial orientation relative to the surveillance camera location and the face are not necessary in-plane with full frontal view.

Chapter 1 – Introduction

Humans are social creatures by nature and engage in a range of behaviours that are influenced by a number of factors which can include genetic make-up, psychological wellbeing, or the natural and cultural environments in which they exist (Baker *et al.*, 2006). While some behaviours are well thought-out and deliberately executed, other behaviours can happen spontaneously without control. Also, some behavioural characteristics are observed in certain groups and not in others; these differences are evident across a range of socio-economic groups and ethnicities (Brown *et al.*, 2011). As such, anti-social behaviour (ASB) is one example of the observed differences in behaviours.

Anti-social behaviour (ASB) is synonymous with a range of behaviours from minor delinquency (harassment and vandalism) to more serious criminal offences (theft, physical violence, acts of terrorism, etc.) (McAtamney & Morgan, 2009). The current widely accepted definition of ASB put forward by the 1998 Crime and Disorder Act 1998 (UK), (Crofts, 2011), defines ASB as a 'behaviour by a person which causes, or is likely to cause, harassment, alarm or distress to one or more persons not of the same household as (the defendant)'. However, as human conduct varies across time, context, and culture (Valsiner, 2007), there are numerous definitions as to what behaviour is considered 'anti-social'. This largely stems from perceptions of what behaviours different communities consider to be problematic at the time (McAtamney & Morgan, 2009). Nonetheless, when we think about behaviours that are antisocial, we usually think about people who have acted in ways that are aggressive, hostile, impulsive, and destructive in nature.

Participation in ASB is common in adolescence. It often occurs as a temporary period of delinquency with some criminal involvement peaking between middle to late adolescence, and desists towards adulthood (Moffitt, 1993). For a small proportion of individuals, there is a continuum of such behaviour patterns, entering into a life-course-persistent ASB (Moffitt, 1993). These individuals engage in ASB that changes over time, that is associated with more serious offending and violence (Smart *et al.*, 2004). It is important to note that ASB differs to anti-social personality disorders (ASPD). Where ASPD is a diagnosed personality disorder with manifestations of ASB, among others

(American Psychiatric Association, 2013). Although ASB is exhibited in persons suffering from mental disorders such as schizophrenia and depression, it can also be present in individuals who do not suffer from any diagnosed mental disorder (Baker *et al.*, 2006).

This relationship between ASB and crime has shown some statistical significance, impacting on the current society. According to the Australian Bureau of Statistics (ABS) (2020a) between the years 2015 and 2019, saw an upwards trend in the number of recorded offenders for homicide and related offences, sexual assault, theft, and weapons possession (Table 1.1). However, there was a decrease in the total number of offenders, due to a marked decline in the number of offenders recorded for illicit drug, property damage and public order offences.

Table 1.1: Number of Austalian Offenders – Recorded crime 2015 – 2019

Summary number offenders recorded by crime, Australia 2015 - 2019					
Principal Offences	**2015**	**2016**	**2017**	**2018**	**2019**
Homicide & related offences	712	702	665	683	752
Acts intended to cause injury	72,721	76,206	78,421	78,308	78,530
Sexual assault & related offences	7,639	7,898	8,123	8,523	8,619
Dangerous/negligent acts	2,135	2,247	2,465	2,131	2,005
Abduction/harassment	4,592	4,857	4,943	3,953	3,939
Robbery/extortion	3,172	3,194	3,388	3,462	3,751
Unlawful entry with intent	11,742	12,297	12,360	12,186	12,242
Theft	39,424	42,060	42,221	41,476	41,234
Fraud/deception	12,509	11,224	11,112	12,146	11,981
Illicit drug offences	81,161	83,204	81,160	77,784	77,074
Weapons/explosives	11,866	12,284	12,117	14,463	15,315
Property damage &environmental pollution	16,399	16,403	16,263	15,732	14,629
Public order offences	69,982	64,014	61,198	61,237	53,560
Offences against justice	25,780	27,172	26,065	27,037	27,458
Miscellaneous offences	21,956	19,556	15,739	16,161	15,046
Total	**381,790**	**383,318**	**376,240**	**375,282**	**366,135**

Table 1.1 shows the number of offenders proceeded against by police across 15 principal offence types between the years 2015 and 2019. Adapted from Australian Bureau of Statistics (2020a).

Conversely, the total number of victims of ASB-related offences had increased from 2014-2019 (see Table 1.2), (ABS, 2020b). During the period of 2018-2019, the number of victims of homicide and related offences (such as attempted murder and manslaughter) increased by 10% from 377 to 416 victims. Despite a decline in unlawful entry with intent that includes property crime, the number of victims of sexual assault, theft and robbery increased over the consecutive years.

Table 1.2: Number of reported victims in Australia – Recorded crime 2015 – 2019

Number of victims of selected Offences 2015 - 2019					
Offences	**2015**	**2016**	**2017**	**2018**	**2019**
Homicide & related offences	418	453	430	377	416
Sexual assault	21,948	23,040	25,837	26,334	26,892
Robbery	8,968	9,412	9,592	10,122	11,775
Unlawful entry with intent	184,007	188,757	176,286	168,050	173,344
Motor vehicle theft	51,525	56,048	52,441	53,324	58,021
Other theft	509,649	537,278	510,392	527,492	569,404
Total	**776,515**	**814,988**	**774,978**	**785,699**	**839,852**

Table 1.2 presents a breakdown of the number of victims of a range of offence type between 2015 and 2019. Adapted from Australian Bureau of Statistics (2020b).

The most harmful type of ASB related crimes is of violence (McAtamney & Morgan, 2009). Violent crimes with the intent of causing (or threatening) physical harm or death to the victim, attracts more attention and debate than any other forms of crime. It is the leading cause of death for people aged between 15 to 44 years and contributes towards the loss of over 1.6 million lives around the world annually (UN World Health Organisation, 2002). The prevalence and frequency of violent behaviour around the world are far greater if we take into account violence that does not lead to death.

One high-profile incident of violence in Australia to play out in the media was the Sydney Lindt Café siege in 2014 (ABC, 2014). At approximately 8:30 am on December 15, 2014, Man Haron Monis walked into the Lindt Café in Martin Place, Sydney and held the staff and customers hostage with a firearm. This incident resulted in mass building evacuations, exclusion zones and the temporary closure of the Sydney's central business district. After a 16-hour siege, Monis shot dead one of the hostages, prompting police 'emergency action' (Scott & Shanahan, 2018). The outcome of this tragedy left three people dead, including Monis himself and several other hostages injured (Thawley & Comley, 2015).

An inquest into the perpetrator had shown he was known to law enforcement and national security agencies from previous encounters with the justice systems. Man Haron Monis who had also been radicalised, was characterised as having paranoid, anti-social tendencies and demonstrated features of narcissistic personality disorder (Wells, 2016). At the time of the siege, Monis was on bail, charged with multiple offences (Scott & Shanahan, 2018), however he was not considered a high security risk, and hence his actions went unforeseen (Thawley & Comley, 2015).

An unnerving aspect of this attack was the site of civilian congregation chosen. The Lindt Café was a small business chain located in the Sydney's central business district of Martin Place, and carried no particular social, political, or religious significance. This crime illustrates the manipulable nature of violence and serves as a reminder that the global society is vulnerable to such opportunistic attacks.

ASB related crime poses significant security concerns. Not only does such behaviour put the safety of civilians at risk, but it also impinges on the quality of life from fear of crime and the exposure to long term psychological damage. The adverse consequences of ASB-related crimes produce a great burden for the victims, family members, and for society at-large. The impacts are multifarious and far reaching beyond the deaths and destruction caused, having economical, psychological, social, and political implications.

On a monetary and economic level, ASB related crimes place financial burdens on the Australian society that are difficult to examine due to the historically small collection of studies that have been attempted on the matter (Webber, 2010). Furthermore, ASB related crimes contain a number of components that can be inherently difficult to measure. The overall financial cost of crime for the country was last estimated at $47.5

billion Australian dollars (AUD) in 2011, equating to 3.4% of national Gross Domestic Product (GDP) (Smith *et al.*, 2014). This is a 33% increase from the previous 2005 estimate of $35.8 billion AUD reported by Rollings (2008) and 49% increase from 2001 where it was approximately $31.8 billion AUD (Mayhew, 2003). While the combined total cost of financial crime was limited to victim assistance, criminal justice, security, insurance, and household precautions, the actual impact does not consider the deteriorating physical and mental health of victims and families, which can also create financial burden. In addition, the unmeasurable components also need to be considered. The trauma of violent crimes can generally be far more harrowing and have a greater impact on individuals and families than the cost of replacing physical items. (Webber, 2010). Nonetheless, the outlay in cost calls for greater preventative measures to reduce the number of incidents caused by antisocial and criminal behaviour (Australian Institute of Criminology [AIC], 2015).

One initiative to tackle crime and ASB that has gained prominent use is closed-circuit television (CCTV). CCTV has been deployed in densely populated areas such as central business and entertainment districts, and on transport systems with the intention variously to prevent and detect criminal offences and improve emergency response time (AIC, 2009). The rise in popularity of its use in Australia has mirrored a global trend towards monitoring public spaces (Wilson, 2008).

CCTV is considered a type of situational crime prevention (SCP) strategy that increases levels of formal surveillance to reduce criminal opportunity and increase perceived risk of offending (Piza *et al.*, 2019).

The main applications of CCTV and other security surveillance cameras include:

- As a crime deterrent - seeks to reduce crime by creating a perception of an elevated risks of apprehension due its presence (Armitage *et al.*, 1999).
- As part of a broader crime reduction strategy with active monitoring and where police can respond quickly to a developing incident.
- For criminal prosecution - equipping modern security cameras with high-resolution video capabilities, which allows for the identification of offenders

during the commission of a crime which can implicate or eliminate them as suspects (Dowling *et al.*, 2019).

- To enhance community safety and cohesion - the visible presence of surveillance cameras can enhance perceptions of safety within the community, and reduce public fear of crime (AIC, 2009).
- Crowd control and management of places through monitoring passenger flows on various transport systems or at mass gatherings to reduce congestion.

CCTV operation in Australia dates back to 1991 but has developed traction over the last 20 years owing to increases in available funding to local governments as part of state, territory, and Commonwealth government crime prevention programs (Hulme *et al.*, 2015). One example being the Safer Streets funding program that committed $50 million towards improved lighting and CCTV in retail, entertainment, commercial precincts, and other projects (Australia National Audit Office, 2015). As such, the proportion of CCTV systems installed by local councils in public spaces increased from 9% in 2005 to 57% in 2014 (Hulme *et al.*, 2015).

Despite continued investments, there are growing concerns with regards to the efficacy in use, particularly for the proactive detection of crime (AIC, 2009). Research studies have shown that CCTV is associated with reductions in property crimes and vehicle crimes whilst demonstrating little effect on the level of violent crimes (Welsh & Farrington, 2008; Piza *et al.*, 2019). The largest and most consistent effects of CCTV were observed in car parks, the success coinciding with other strategies such as improved street lighting and signage notifying the public of surveillance cameras (Welsh & Farrington, 2004; Welsh & Farrington, 2009). Given the nature of their application, CCTV systems vary considerably with respect to their management, operation practices and technology (Wilson and Sutton 2003).

There also exist several limitations: 1. Not all CCTV are actively monitored. A survey by Hulme *et al*. (2015) reported at least 61% of systems operated by councils are unmonitored, with a further “15 per cent were occasionally monitored by an operator during business hours”. 2. The physical and psychological limitations of human operators monitoring CCTV images. Due to the overwhelming amount of visual information from camera feeds, affords only a small fraction of the cameras being monitored at any given time. Additionally, the required attention and sustained level of alertness (Warm *et al.*, 2008) for extended periods of time imposes considerable cognitive demands that greatly influences where, when and how operators monitor and detect significant events (Ainsworth, 2002; Velastin *et al.*, 2006; Donald & Donald, 2019).

There is a gross misconception that the use of CCTV systems can deter crimes simply by being viewed in plain sight. By virtue, cameras are only useful as the intelligence provided to them (Isnard, 2001). Unfortunately, the extent to which CCTV has been valuable for criminal investigations has been for post-incident investigations (Ashby, 2017). Despite current limitations, there are numerous potential reasons for growth.

As electronic surveillance is becoming a ubiquitous feature of daily life, the need for faster and more intuitive security applications systems are required to increase its utility. With automated detection methods of surveillance for pre-response have become an area of interest (Wiliem *et al.*, 2012), an approach in this use may be most effective when implemented in conjunction with other intelligence systems to enhance proactive security objectives. As such is the use of emotional intelligence with surveillance technology programs to flag individuals that may be of concern (Wang & Fang, 2008). Studies have explored the utility of CCTV surveillance recording to detect behavioural cues from the limbs and body (Troscianko *et al.*, 2004) to make accurate predictions of antisocial and other criminal activity. The results were inconclusive because the study failed to take into consideration the emotional constituents of behaviour. It has been widely documented that criminal offenders have poor emotional control (Sharma *et al.*, 2015) that correlates with observable behaviours (Chaiken *et al.*, 1994). A research project conducted by Canter and Ioannou (2004) reported a range of emotions experienced by criminal offenders during the commission of crimes. The study found certain emotions to be significantly correlated with different crimes, in particular intense negative emotions were interlinked to interpersonal violence. The fact that certain emotions are synonymous with certain criminal acts warrants further investigations into the development of systems for the prediction of such behaviour.

Research has shifted towards analysis of the face (Grant & Williams, 2011) which serves as a natural analogue for emotional expression. Facial expression recognition (FER) can play a role in crime prevention as gauged facial expressions are valid reflections of a person's mental or emotional state and allows us to predict future behaviours (Ahn *et al.*, 2010). FER is already an active research topic in the fields of psychology, computer vision, and pattern recognition and may be of interest to create a system based on visual indicators of emotion recognised from CCTV and other video surveillance system images. However, a facial recognition program tailored to evaluate facial behaviour for forensic and surveillance applications can be met if patterns of emotions in general can be detected. Research is required to understand the inherent nature of emotions to link the constructs of emotional facial expressions with human behaviour. Hence this investigation starts with the basic emotions.

1.1 Emotion Function, Generation, and Actions

Subjectively, there are very few psychological phenomena that compare with emotion. The implicit knowledge about emotion is that it is universally felt, and as such most people believe they already know a great deal about emotions. For example, we believe that emotions are powerful internal forces that affect our thoughts, behaviours, and decisions, even when we prefer, they did not. Some emotions make us feel good and others makes us feel bad, some people are just more emotional than others.

Attempting to define emotion is a not an easy task, given emotions are idiosyncratic, where emotional expression and experience are not always consistent between individuals. A survey by Kleinginna and Kleinginna (1981) evaluated 92 definitions of emotion from textbooks and journals, as did Izard (2010) who canvassed prominent emotion theorists and researchers on their working definitions of emotion. The conclusion that both studies reported was that the term "emotion" lacks a consensus. Despite failed attempts to identify the scientific criteria that distinguish one emotion from the next (Izard, 2010), there is considerable agreement that emotion is best viewed conceptually as a coordinated set of responses to events that yield significance to the organism (Arnold, 1960; Plutchik, 1980; Smith & Lazarus, 1990). These response sets may involve cognitive, experiential, physiological, and behavioural manifestations that aim to orchestrate the best possible response to deal with those events (Nesse, 1990; Smith & Lazarus, 1990). In literature, several approaches for modelling emotions have been proposed stemming from different research fields that have focused on different aspects of emotion (James, 1884; Schachter & Singer, 1962; Ekman *et al.*, 1972; Ellsworth &

Scherer, 2003; Fox, 2008; Lindquist *et al.*, 2012). These modelling approaches of emotions are described in the following sections.

1.1.1 Function of Emotions

The first major synthesizer of ideas about the nature of emotion was Charles Darwin who ascribed an evolutionary approach to the functions of emotion. His book "The Expression of Emotions in Man and Animals" (1872) suggests that not only did evolution apply to that of physical structures, but that mental states and behaviours also were wired to meet environmental demands.

The common reoccurring survival issues faced by most animal species include, among others, food source, reproduction, shelter, and protection from threats (Smith & Lazarus, 1990; Haselton & Ketelaar, 2006). For our ancestors to overcome those challenges, the physiological, psychological, and behavioural parameters were adjusted in ways that increase their capacity and tendency to respond adaptively to these situations. This resulted in the development of distinct innate mechanisms to address those problems (Haselton & Ketelaar, 2006) along with the evolution of 'basic' emotions accompanying those mechanisms; anger, fear, sadness, joy, surprise and disgust (Tomkins, 1962; Ekman *et al.*, 1972; Plutchik, 1980).

Darwin (1872) observed in humans and other animal species, the show of emotion through similar behaviours. This was illustrated by comparing and analysing sketches and photographs of animals and people in different emotional states to reveal cross-species similarities. Whilst it was maintained that many emotional expressions exhibited (e.g., tears when upset or baring the teeth when angry) were vestigial patterns of action (Darwin, 1872), they also serve social functions, deriving from the fact they were an outward manifestation of an inner state (Hess & Thibault, 2009).

The signalling of trait-like tendencies enabled rapid non-verbal transmission of relevant information, such as whether an encounter is harmful or beneficial could help solve social problems by evoking responses from others such as to flee from nearby danger. Thus, the utility of emotion served two purposes in general: 1. To motivate action, in response to either deviations from, or opportunities towards an ideal state, and 2. Enhance social interactions (Keltner & Haidt, 2001).

The idea that different emotions serve different survival-related goals was functional in the past context of primitive situations. However, in the modern world where one is rarely confronted by clear-cut primordial threats, instead encounter many smaller threats of increasing complexity. Overtime, humans developed elaborate neural systems to support more varied responses, and emotional agents to solve a much wider range of adaptive problems to better facilitate increasing demands of the developing world. This set the foundation for subsequent investigation to understanding emotion beyond a surface level.

1.1.2 Generation of Emotions

William James (1884) and Carl Lange (1885) independently presented a sequence explaining the cause-and-effect relationship between emotions and physiological events. They regarded emotions as adaptive behavioural and physiological response tendencies that are called forth directly by evolutionarily significant situations (Gross, 1998).

Their theory, known as the James-Lange theory of emotion posited that sensory feedback from bodily responses (such as increased heart rate, respiration, sweating and trembling) accounted for the quality of emotional experiences. The sequence begins with a stimulus which elicits a specific physiological response, and as an individual experiences these physiological changes, emotion is felt (Figure 1.1). Therefore, the experience of emotions (such as fear, sadness, and joy) is viewed to occur after physiological arousal has occurred and that each emotion adheres to a slightly different set of physiological patterns. For example, the feeling of sadness in consequence of crying or happiness proceeding laughter.

Figure 1.1: James-Lange Theory of emotion sequence

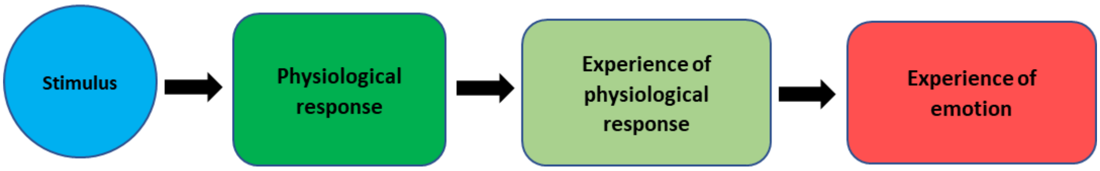


Figure 1.1. explains the James-Lange theory of emotion (1890) which begins with an external stimulus that triggers a specific physiological response, and as an individual experiences these physiological changes, manifests as an emotion.

In his earlier research, James (1884 and 1890) acknowledged that expressive behaviour (e.g., crying) in addition to other bodily responses contributed to the feelings of various emotions. However, in the ensuing decades discussions focused more on narrowing the visceral changes (Laird & Lacasse, 2014). As such, an oversimplified model led to several critiques particularly by Walter Cannon (1927) who argued the theory failed to explain the same visceral changes that occur in different emotional and non-emotional states for e.g., fever, low blood sugar and exposure to cold. Another critique centred around the fact the theory could not account for the delay in visceral changes for emotions that could otherwise occur instantaneously (Vianna *et al.*, 2006).

Cannon (1914) studied emotions by producing emotional experiences in laboratory animals, proposing a thalamic theory of emotional experience (Dror, 2013). The integrated works of Philip Bard (1934) identified the essential roles of the thalamus and the cortex of the brain had in the generation of emotion to develop the Cannon–Bard theory. It assumed the following sequence (Figure 1.2):

Figure 1.2: Cannon-Bard Theory of emotion sequence

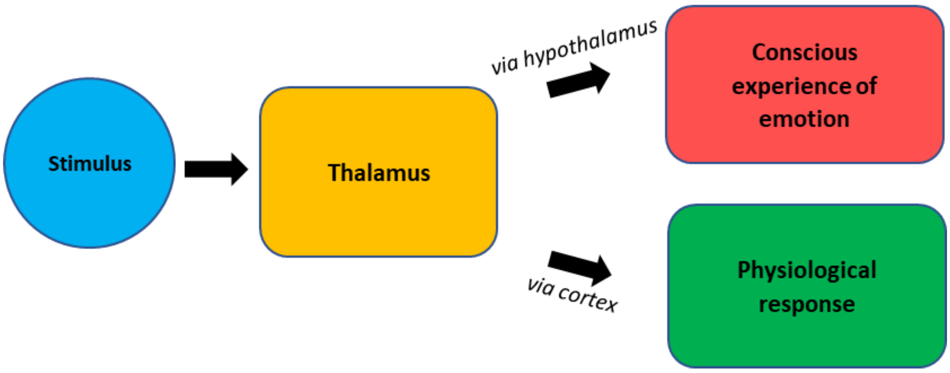


Figure 1.2 in response to an emotional stimulus, identification (experience) of an emotion *occurs at the same time as the activation of bodily responses.*

Under the Cannon-Bard model, physiological arousal and emotional experience occur simultaneously and autonomously, like blushing when feeling embarrassed. This is due to the input of sensory information to the thalamus which is then sent to various parts of the brain that control emotional and physiological responses (Cannon, 1927).

Stanley Schachter and Jerome Singer (1962) presented a cognitive interpretation, incorporating elements of both the James-Lange and Cannon-Bard theories of emotion to create a model known as the Two-Factor Theory (Figure 1.3). They proposed that the feeling of emotion is contingent on two processes: physiological arousal and the cognitive interpretation of that arousal. The structural model drew parallels to the James-Lange model; however, an important distinction is the cognitive attribution. Since the physiological profiles are similar across a wide variety of emotions, necessitating the cognitive element to bridge the gap between non-specific feedback received from bodily responses and the specificity of the emotion felt.

Figure 1.3: Schacter-Singer Two-Factor Theory (1962) of emotion sequence

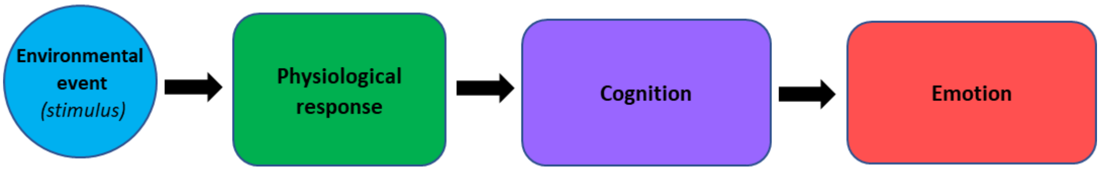


Figure 1.3 illustrates the emotion sequence which involves an event stimulus eliciting a physiological response, that is then cognitively interpreted and labelled, resulting in the generation of an emotion.

Appraisal theorists go further to consider emotions as processes, rather than states. In appraisal theories of emotion, emotions are activated by the cognitive appraisal of personally relevant circumstances (Arnold, 1960; Smith & Lazarus, 1990). Furthermore, the quality and intensity of emotion elicited is not dependent upon the situation itself, but the person's subjective evaluation in terms of a set of appraisal dimensions (Schmidt *et al*., 2010).

An emotional episode begins with the encounter of a stimulus (this can be either real or imagined). Attention is deployed and the event stimulus is appraised with respect to the subject's concerns (Ellsworth & Scherer, 2003). The event is evaluated as either being positive or negative. This appraisal of the emotion eliciting stimuli will automatically engage in a process of liking or disliking and is regarded as the experience of emotion (Frijda, 1986). This evaluation leads to an integrated action referred to as a motivational tendency and is often accompanied by physiological and behavioural changes (Frijda, 1986) (Figure 1.4).

Figure 1.4: Appraisal Theory (1986) of emotion sequence

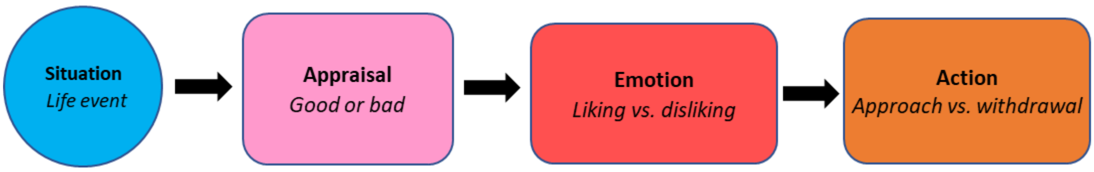


Figure 1.4 according to the appraisal theorists, the generation of an emotion occurs as a process and sequence over time: 1. Situation that is emotionally relevant (real or imagined). 2. The situation is evaluated and interpreted (appraisal). 3. An emotional response is generated. 4. The response will elicit an action which is referred to as a motivational tendency.

Lazarus (1991) identified two major types of appraisal methods: primary and secondary appraisal. Primary appraisals principally relate to the domains of arousal and valence of an emotion. According to the circumplex model of emotions (Russell, 1980), each basic emotion is postulated to be a combination of these two domains, in differing degrees. If the situation is beneficial to the individual's current goal (i.e., motivationally congruent), the experience of emotion is pleasant; whereas if the situation is interfering with ongoing plans (i.e., motivationally incongruent), the emotional experience will be an unpleasant one. Secondary appraisal then further categorises within either a positive or negative emotion spectrum according to the evaluated coping potential (Parkinson, 1997). Distinctive configurations of patterns from primary and secondary appraisals form unique core relational themes that are associated with an emotion (Smith & Lazarus, 1993). For example, sadness is represented by the core relational theme of "irrevocable loss", whereas happiness is characterized by the core relational theme of “success” or progress toward to realisation of a goal (Smith & Lazarus, 1993).

It is believed emotions arise after considerable meaning analysis as such, calls upon a coordinated set of behavioural, experiential, and physiological response tendencies that together influence how one responds to perceived challenges and opportunities. The process is continuous and recursive. Because these multi-componential processes unfold over time, they permit the regulation of emotion at any time in the emotion generative process (Gross, 2002).

As such, ideas surrounding emotion have become vastly complex to be distilled into one emotional schema. This is reflected in the wide range of available perspectives on emotion. However, modern theories of emotion have acknowledged the interactions between cognition and emotion for the interpretation of events (Arnold, 1960; Mandler, 1975; Scherer, 1985), decision making (Damasio, 1994) and goal related behaviour (Plutchik, 1984; Frijda, 1988; Lowe & Ziemke, 2011). Recent studies have extended research towards neurobiological mechanism underpinning emotions (Fossati, 2012; Lindquist *et al*., 2012; Kragel & LaBar, 2016).

1.1.3 Emotion and the Brain

Paul D. Maclean (1952) first coined the term limbic system to refer to a collection of interconnected brain structures that have been shown to display high levels of neural activity during emotional experience. His model was derived from Broca’s limbic lobe (1878) and formed part of his triune brain model that largely reflected an evolutionary view of human brain development. This limbic system ‘concept’ was a partition of the brain involved in behavioural and emotional responses and includes the hypothalamus, the amygdala, the thalamus, and the hippocampus (Figure 1.5). The field of affective neuroscience has since advanced and the implication of other structures (i.e., anterior cingulate cortex, orbitofrontal cortices, and insula) contributing to emotional processes

(Roxo *et al*., 2011; Fossati, 2012). Furthermore, neuroimaging data have indicated that emotion categories are not contained within any one region but represented through neural activity across multiple brain regions (Kragel & LaBar, 2016).

The thalamus serves as a sensory relay centre, with neural projections to the amygdala and other cortical areas. The structure plays an important role when it comes to monitoring and updating current information within a changing environment. Its functional properties include monitoring and updating mental constructs in contrast to previous views to address ongoing challenges (Wolff & Vann, 2019). This ability to continuously track changes offers the capacity to adapt to the changing environmental demands that is needed for successful performance and survival (Wolff & Vann, 2019).

The hypothalamus regulates fundamental aspects of physiological homeostasis and behaviour (Xie & Dorsky, 2017). One primary concern is maintaining internal body balance or homeostasis. This balance can be altered substantially during emotional states and duress. Upon generated feelings and thoughts of action which can cause perturbations to homeostasis, afferent neural signals (e.g., amygdala) are sent to the hypothalamus. This initiates activation of autonomic nervous stress systems ('fight or flight') and neuroendocrine stimulation of various glands either to inhibit or to release hormones which bring about behavioural and physiological changes of state (Germann & Stanfield, 2005; Smith & Vale, 2006). The hypothalamus and other structures involved in the stress response also intersect with circuits involved in memory and reward, which also modulate stress responses with respect to prior experience and anticipated outcomes (Ulrich-Lai & Herman, 2009).

Figure 1.5. The Limbic structure

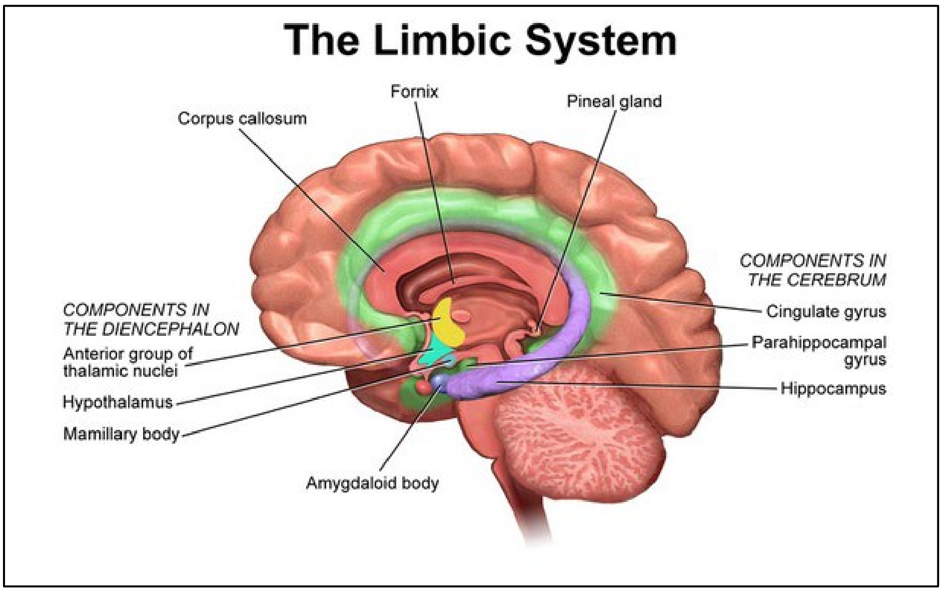


Figure 1.5 displays an image of the Limbic structure. Emotion is regulated by brain structures located in interior regions such as the hypothalamus, amygdala, hippocampus, and cingulate cortex. These subcortical structures lead to a combined visceral and cognitive outcome of the emotion experience. Image adapted from Blausen.com staff (2016).

A key area included in Broca's limbic lobe (1878) is the cingulate cortex, the structure which is highly influential in linking behavioural outcomes to motivation. It is implicated in emotion because it is involved in linking reward and punishment information, which elicits emotional responses, to behaviour, and to actions (Rolls, 2019). The anterior cingulate region of the cortex receives inputs from the amygdala and orbitofrontal cortex concerning reward and punishment information with respect to actions performed. It uses this information for learning that action. The posterior regions receive input from the parietal cortex and have connections with the hippocampus. As such use the information related to action-outcome learning to project visual spatial information to the hippocampus, where it can be combined with object and reward-related information to form episodic memories (Rolls, 2019). The hippocampus is a medial temporal lobe structure that is associated with learning, episodic memory processing and spatial cognition. During emotional situations, the amygdala governs the hippocampal encoding and storage of episodic representations of the emotionally significant events. Which then can in turn influence the amygdala response during subsequent encounters with the emotional stimuli (Phelps, 2004).

The amygdala is known to play a critical role in emotional perception, learning, and memory (Phelps & LeDoux, 2005). The structure has extensive connection throughout the brain and is positioned to prime and coordinate visceral and behavioural responses to psychological stress (Arnsten, 2015). Owing to its susceptibility to stressful conditions, the amygdala was initially implicated in fear related processes (Ledoux, 2002), but has shown to be critical for processing the affective content of stimuli across positive and negative dimensions. Bonnet *et al*. (2015) conducted a study which used functional magnetic resonance brain imaging (fMRI) to examine regional brain activity of participants exposed to neutral, positive, and negative valence stimuli. Results indicated the amygdala is sensitive to emotion arousing cues, increasing in activity with greater arousal, which suggests its role in tagging salient cues in the environment. As such, preferential processing of emotionally relevant stimuli, can shift awareness to assure that information of importance is more likely to influence behaviour (Phelps & LeDoux, 2005).

The prefrontal cortex (PFC) is the most evolved brain region that underlies important higher order executive functions such as planning, reasoning, decision making and social control. The PFC plays an essential role in the generation and regulation of thoughts, emotion, and actions in accordance with internal goals (Arnsten, 2009). Regions of the PFC that regulate emotional responses are situated ventrally and medially, with projections to subcortical structures (i.e., amygdala, nucleus accumbens and the hypothalamus). Regions that regulate thoughts and actions are situated more dorsally and laterally (Arnsten, 2009). This is of particular significance as impairments in the PFC can result in deficits in emotions and foster maladaptive behaviours including aggressive and antisocial behaviours (Siever, 2008; Choy *et al*., 2018).

1.1.4 Emotional Expressions

Emotions play a crucial role in our everyday lives. During social interactions emotions are expressed through both verbal and nonverbal means. This replete of emotional exchange has signalling value to provide information about the disposition of oneself and others, and of the situation (Hareli & Hess, 2012). The signals can include facial expressions (Ekman, 1972), speech prosody (Frick, 1985; Banse & Scherer, 1996) and whole-body behaviours (Tracy & Robins, 2007).

The prosody of speech includes vocal elements such as pitch, loudness (intensity) (Frick, 1985), and rhythm (Banse & Scherer, 1996; Grandjean *et al*., 2006) and are influenced by physiological parameters (e.g., heart rate, blood flow and muscle tension) that change depending on a person's emotional state (Schirmer & Kotz, 2006). It has been shown that different emotions and moods vary in tonal quality and speech patterns. An analysis of vocal behaviour by Banse and Scherer (1996) identified specific patterns and combinations of acoustic parameters of the voice which signal discrete emotional states. These results were obtained from spectrographic analysis of role-played emotional states of adults to uncover the underlying acoustic parameters associated with the emotional state of the speaker. Other studies have reported higher levels of pitch and amplitude associated with high-arousal emotions such as fear, joy, and anger compared to lower-arousal emotions such as sadness with intensity increase for anger, fear and decrease in sadness (Scherer *et al*., 1991; Johnstone & Scherer, 2000).

Studies of body movement often involve tracking the position of each body part over time. One form of tracking human motion involves marking several illuminated points or stripes on a moving figure positioned on the main body parts and joints (Johansson, 1973). These studies have linked expressions of pride to expansive behavioural body postures (Tracy & Robins, 2007). Whilst embarrassment is reflected in diminutive behavioural body postures (Keltner & Buswell, 1997).

To date, research on emotion-specific expression has emphasised the face (Izard, 1971; Ekman, 2003; Scherer *et al*., 2019). Facial expressions formed by configurations of different micromotor movements in the face that are used to infer a personal emotional state and indicate an individual’s intentions within a social situation (Fridlund, 1991). Darwin (1872) was the first to propose that some facial expressions of emotion have their origins in evolution and therefore are universally expressed. When examining the musculature of the human face, he observed the same consistent muscle contractions and facial movements for simple and complex emotion. This idea spawned rich domains of enquiry into facial expressions of certain emotional states (Tomkins & McCarter, 1964; Ekman & Friesen, 1971).

Judgment studies focused on whether perceivers can infer emotions from facial images displaying different emotional expression and found strong agreement in cross cultural recognition studies (Ekman & Friesen, 1971; Izard, 1971). Others examined emotion related activations of facial muscles using electromyography (EMG) (Cacioppo & Petty, 1986; Dimberg, 1990; Root & Stephens, 2003; Rymarczyk *et al*., 2016). These studies have shown increases in *corrugator supercilii* (brow) muscle activity during anger exposure (Cacioppo & Petty, 1986; Dimberg, 1990), *corrugator supercilii*, *orbicularis oculi* (eyes) and *levator labii* (upper lip) muscles with disgust, and a combination of *zygomaticus* (cheek), *orbicularis oculi* (eyes) and *corrugator supercilii* (brow) muscle activity associated with positive affects (Cacioppo & Petty, 1986; Root & Stephens, 2003).

However, the intrusive measure of electrode placement for EMG has progressed to the development of observer-based measurement systems such as the Facial Action Coding System (FACS) to taxonomize visual facial behaviours (Ekman & Friesen, 1978). A study by Matsumoto and Willingham (2009) used FACS to illustrate concordance in expressions between the congenitally blind, noncongenitally blind, and sighted athletes in the display of happiness and contempt. Du and Martinez (2015) identified stereotypical facial patterns of movements of 17 compound (blended) expressions using FACS. These compound emotions are emotions composed of two or more categories (such as happily surprised or sadly fearful). Furthermore, these emotions were found to be consistently produced across cultures suggesting a much larger number of universal expressions than initially postulated.

Despite numerous facial expressions being investigated, it is widely supported within the scientific community that there are seven basic emotional expressions: joy, sadness, fear, disgust, anger, surprise and contempt. Where each facial expression phenotype is universally expressed and interpreted synonymously across all cultures (Keltner & Ekman, 2000; Matsumoto & Hwang, 2011). As such, the use of prototypical emotional expressions has also been imported into other scientific disciplines with an interest in understanding emotions, such as neuroscience and artificial intelligence (AI).

1.1.5 Emotions and Antisocial Behaviour

Emotions play an important role in the cultivation of prosocial behaviours (actions intended to help others), prosocial motivations and values (Eisenberg, 1986). Furthermore, they contribute to social connection and interpersonal understanding through empathy. When emotions are not functioning properly, they lose their ability to promote positive social connection, which leads to maladjusted behaviour patterns that foster ASB (Baumeister & Lobbestael, 2011). Individuals involved in ASB appear to consistently exhibit difficulties with emotional affect and deficits in behavioural control that are particularly exacerbated under emotional conditions. As such, these individuals will show a propensity towards impulsive behaviours under heightened emotional states, otherwise known as "mood-based rash action" (Cyders & Smith, 2008). This is often seen when antisocial people place themselves in risky, stressful, or dangerous situations more frequently than other people (Cyders & Smith, 2008).

Robert Agnew (1992) developed the general strain theory (GST) as an explanation of antisocial behaviour as a consequence of strain, and its relevance to crime and violence. Agnew's (1992) GST argues that strain (i.e., stress) causes individuals to experience a variety of negative emotional states such as anger, depression, anxiety, and fear. These negative emotions create a disposition for corrective action, which may be alleviated through engaging in delinquent and criminal actions (Ganem, 2010).

There are three categories of strain which may impact deviant outcomes. The first type is failure to achieve goals, which centres around the theme of goal blockage that is measured as the resultant gap between the expectant and actual goals achieved. The second type of strain involves the removal or threat of removal of a positively valued stimulus (e.g., the loss of a job or house), and the third is the confrontation of a noxious or a negatively valued stimulus (e.g., individual who is subjected to constant bullying). The negative feelings induced by these strains could lead an individual to seek criminal behaviours as a means to cope with their emotions (Agnew, 1992). Merits in the GST have been found in several studies on youth (Piquero & Sealock, 2000; Moon & Morash, 2013) and young adult offending (Ostrowsky & Messner, 2005) which indicated strains have significant effects on property and violent offending.

It is also believed that certain strains and stressful situations increase the likelihood of crime, for example: parental rejection or poor domestic household circumstances; negative school experience; abusive peer relations; criminal victimization; and experiences with prejudice and discrimination (Peck, 2013). However not all individuals who experience strain respond in a criminal manner. Agnew (1992) acknowledge there are a number of elements that affect whether one will engage in crime. However, the main determining factor is the coping strategies mediated and available resources (e.g., support networks) at one's disposal.

Among processes thought to influence antisocial behaviour, emotional intelligence (EI) has emerged as a potentially relevant variable. Emotional intelligence is the ability to perceive, use, understand, and manage emotions (Gómez-Leal *et al*., 2018). Persons with high EI levels are more able to moderate their emotions and are less impulsive. Whereas individuals with low EI levels are associated with lack of emotional control, are more impulsive, thus are more susceptible to aggressive and offending behaviour (Sample, 2017). The reduced capacity to regulate and manage emotions could possibly sustain the offending pattern of such behaviours.

Sharma and colleagues (2015) investigated the relationship between EI and criminal behaviour. Their study reported that criminals had significantly lower EI compared to a normal control group meaning that they were more susceptible and more likely to engage in dangerous and risky behaviour. Furthermore, a systematic review conducted of literature carried out by García-Sancho *et al*. (2014) looking specifically at the relationship between EI and aggression, reported that just over 94% of the listed studies indicated a negative relationship between of EI and aggressive behaviour, regardless of social-cultural context, age, or type of aggression.

Aggression and other forms of overt externalised behaviour have shown to reach their peak in children between the ages two and three (Trentacosta & Shaw, 2009). In some children, high levels of aggression continuously remain through childhood with delinquency and forms of ASB (Trentacosta & Shaw, 2009). This may be due to the failure in childhood development of self-regulatory mechanisms to shift focus and inhibit attention, to attenuate behaviour resulting from increases in emotion. As a result, individuals may experience difficulties in processing emotion, have impaired cognitive abilities, a difficult temperament, and possess elevated thresholds for emotional reactivity (van Goozen, 2015).

Given the likelihood of certain individuals to engage in criminal acts when in a state of heightened emotional reactivity that is exacerbated by certain stressors, the recognition of emotions may serve as a useful behavioural indicator of imminent acts of violence and other ASB-related crimes. The potential development of an emotional signalling system would allow for transmission of information about an individual's intentions, status or as a warning to others in the surrounding environment. Given that the face is the most accessible visible social part of the human body that can facilitate in the prevention of crime, as facial expressions can be used as markers of emotional states that are indicative of violence and other antisocial behaviour. The idea of using facial expressions to measure emotion has been chosen for the present research because of its immediate applicability in CCTV and other visual surveillance.

1.2 Emotional Facial Expressions

The human face is a rich source of information from which observers can make a number of inferences – about identity, gender, age, race, emotional state, and behavioural intent (Fridlund, 1991; Yankouskaya *et al*., 2012; Jack & Schyns, 2015). It is the most accessible visible social part of the human body and as such, it is the focus of visual attention in most healthy individuals. When individuals engage in social interaction, their faces tend to move in a complex manner combining rigid rotational and non-rigid movements to convey messages (O'Toole *et al*., 2002). A furrowed brow, inclination of the head, the pursing of lips, faces 'speak' through movements, as such there is a dynamic exchange of specific patterns of information through facial expressions (FE) to achieve a mutual understanding between individuals.

1.2.1 Muscles of Facial Expressions

The muscles of FE are important as they are responsible for non-verbal communication between humans. The facial muscles are located in the subcutaneous tissue, they are generally thin and concealed by fat (Westbrook *et al*., 2020). Facial muscles originate on the surface of the skull, however unlike other skeletal muscles which inserts onto another bone, they insert into connective tissue, skin, and other muscles. Hence, when these muscles contract, not only do they displace the surface skin, but they also displace fat pads and other facial muscles (Zarins, 2019). The contractions result in contortions of facial features such as eyebrows, lips, and skin texture, giving rise to wrinkles, furrows and ridges. A combination of these changes is known as a FE (Zarins, 2019). These changes of muscular activities are brief, lasting for a few seconds (Ekman, 2003).

The facial muscles are positioned around facial openings (i.e., eyes, nose, and mouth) and configured to enable movements not only to regulate the width of facial openings but also make them more expressive. The facial regions and associated muscles that contribute to FE include:

Forehead regions – The *occipitofrontalis* muscle corrugates the forehead by elevating the eyebrows and scalp. The muscle consists of two muscle bellies, the frontal and an occipital belly that are connected by a broad tendinous sheath called the *epicranial aponeurosis*, or *galea aponeurosis* (Zarins, 2019).

Oculi regions – The *orbicularis oculi* muscle surrounds the eye socket and extends into the eyelid. It has three distinct parts – palpebral (gently closes the eyelids), lacrimal (involved in the drainage of tears) and orbital (tightly closes the eyelids) parts. The palpebral area lies at the centre of the sphincter muscle and forms the eyelids with the orbital region encasing it concentrically. Additionally, there are several small facial muscles e.g., *corrugator supercilii*, which are the prime mover of the eyebrows, and the *depressor supercilii* both of which act to draw the eyebrows downwards and together producing vertical frown lines (Yu & Wang, 2020).

Nasal regions – The muscles of the nasal regions include the *nasalis* which covers the nose. It is split into two parts; transverse and alar portions which compress and opens the nares, respectively. The *procerus* is the most superior of the nasal muscles and lies superficially to the other muscles of FE. This muscle is used to wrinkle up the nose which narrows the nostrils (Nguyen & Duong, 2020).

Oral region – The oral group are responsible for movements of the mouth and lips. The fibres of the *orbicularis oris* enclose the opening to the oral cavity. However, there are other muscles that act on the lips and mouth, and anatomically they can be divided into upper and lower groups. The upper group contains the *risorius*; *zygomaticus major*; the *zygomaticus minor* which helps form the shape of the cheeks; *levator labii superioris*, *levator labii superioris alaeque nasi* help dilate the nostrils and elevates the upper lip;

and *levator anguli oris* which elevates the upper lip and angle of mouth (Nguyen & Duong, 2020).

The lower group contains the *depressor anguli oris*, *depressor labii inferioris* which lowers the lips and depresses the angle of the mouth. The *mentalis* raises the chin thrusting the lower lips to pout (Nguyen & Duong, 2020).

The facial muscle tissues have a common embryonic origin in the 2nd pharyngeal arch and are innervated by the seventh (VII) cranial (facial) nerve which derives signals from the cerebral cortex (Dulak & Naqvi, 2020; Westbrook *et al*., 2020). The facial nerve emerges between the pons and medulla, and courses through the facial canal in the temporal bone, exiting through the stylomastoid foramen into the parotid gland where it splits off into 5 branches (temporal, zygomatic, buccal, mandibular and cervical) to innervate the muscles of facial expressions (Dulak & Naqvi, 2020). There are two distinct brain systems that mediate FE: a cortical system that is responsible for voluntary expressions and a sub-cortical system responsible for emotional expressions (Gothard, 2014).

1.2.2 Facial Expressions of Emotion

Darwin (1872) had emphasized the use of emotion expressions for communicative purposes, and as such proposed there must be universal laws for emotional expressions that are recognised across all cultures. Using cross-cultural validation for his observations, he was the first to use judgment studies for the assessment of emotional expressions. The methodology included showing photographs of FE to observers and noted what emotions they attributed to each expression. In his book Darwin (1872) had discussed many expressions of emotional states, notwithstanding commonly accepted states, such as joy and anger, but also such states as patience and sulkiness. However, he did not single out specific emotions as basic.

Expansion of research in the area used similar judgment techniques to articulate his original research. For example, Izard's (1971) study showing photographs of expressions of eight emotion categories to nine different cultures. Whereas cross the board, participants showed 70% agreement with identified emotions. Likewise, Ekman and colleagues (1971) reported cross-cultural consistency with the Fore people in Papua New

Guinea who without being primed were able to correctly judge and express the same FE of emotion as Western cultures beyond levels of chance.

Further analysis of facial behaviour by Ekman (2003) identified specific patterns of facial activity that can be used to infer a person's emotional state in much the same way that a fingerprint can be used to uniquely recognise a person. A discrete emotions system was identified to have at least seven basic emotional expressions displayed among all humans: joy, sadness, surprise, fear, anger, disgust and contempt (Figure 1.6). Where each facial expression phenotype is universally expressed and interpreted synonymously across all cultures (Keltner & Ekman, 2000).

Figure 1.6: Basic emotional facial expression phenotypes

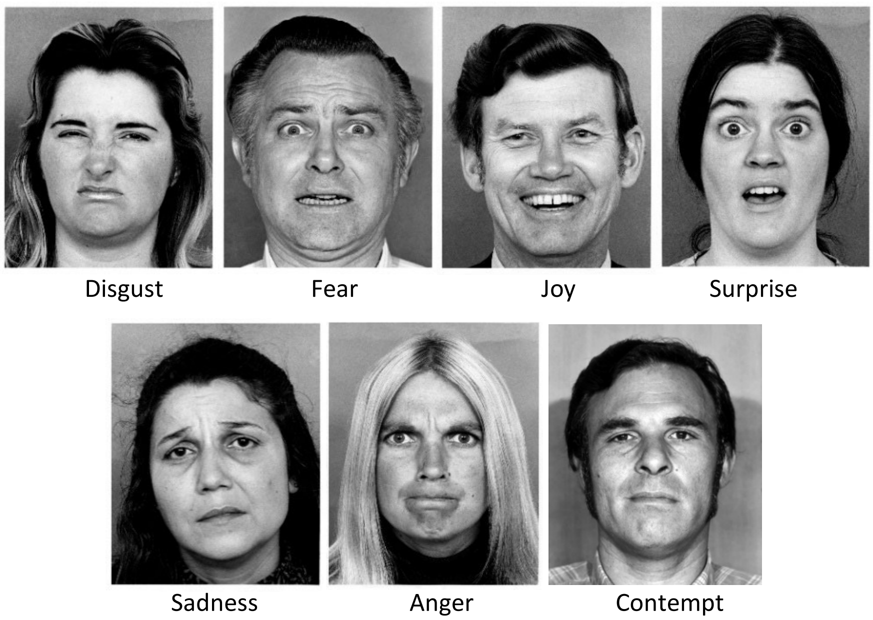


Figure 1.6 illustrates the seven different facial expressions of basic emotions as listed, starting from the top running from left to right: Disgust; Fear; Joy; Surprise; Sadness; Anger; Contempt. Image adapted from Ekman and Friesen (2003). Copyright © Dr. Paul Ekman 2003.

Studies regarding the production and recognition of basic emotional expression can be drawn from comparative research (Matsumoto, 1990), studies of infant FE (Nelson *et al*., 2006; Maack *et al*., 2017), and neurological studies (Rinn, 1984; Quiñones *et al*., 2011). Over the last few decades, the preponderance of basic emotional expression research has been used to identify neurological or psychiatric disorders (Quiñones *et al*., 2011), along with conceptual frameworks for uses in healthcare (Tivatansakul *et al*., 2014; Ragsdale *et al*., 2016), marketing (Shergill *et al*., 2008) and gaming (Akbar *et al*., 2019).

Contrastingly, social constructionist view of emotion believe that facial behaviour originates from social contexts and therefore is learned during socialising in the context of the culture in which they are raised in (Lindquist, 2013; Barrett, 2014). This line of theory has found support throughout many perceptual studies revitalising the debate about innateness of basic emotions. Gendron *et al*. (2014) reported cultural variability in perceptions of emotional FE from individuals from the Himba ethnic group in Namibia. A tribe with limited contact outside their community who did not perceive FE according to the universal patterns when it came to sorting facial images into groups by emotion type. Jack *et al*. (2012) showed that individuals from Western and Eastern cultures displayed discordance in perceptions of facial movements to those considered to be universal emotions. Although, a possible explanation could be the differences in scanning behaviour that was observed. Western observers were shown to frequently look between the eyes and the mouth, whilst East Asian observers spent more time fixating on the eye region. Which suggests cultural differences in coding and encoding of expression rather than the emotion itself (Reyes *et al*., 2018).

Despite debates regarding universal or social construction of emotion studies. The use of discrete emotion systems remains the mainstream for facial analysis research. Furthermore, researchers have acknowledged the influence of environmental, cultural and societal factors, in governing certain aspects of FE (Ekman & Friesen, 1969; Ekman, 1972; Matsumoto, 1990; Engelmann & Pogosyan, 2013). Because FE play a central role in communicating emotional and social information, several factors must be considered which can influence the degree of variations in facial expressions.

1.2.3 Cultural Differences

As countries around the world become increasingly multicultural, countless societies have emerged with various communities, each characterised by having their own respective set of beliefs, values, and way of life. Cultural differences in various aspects of emotion have been studied and reported, an important aspect being the emotional arousal level (Lim, 2016). Western cultures display of emotions are linked to high arousal of an energetic state, which are valued more and therefore promoted. By contrast, Eastern cultures have a preferential tendency to experience emotions linked to low arousal (Lim, 2016). The differences in display of behaviours are attributed by the distinct characteristics of individualist and collectivist cultures that likewise influence the prevalence and strength of cultural displays. In Eastern or collectivist culture, which emphasises values for group harmony and cohesion, conforming to others is considered desirable for social cohesion (Matsumoto, 2007). The use of low arousal emotions tends to work favourably in social situations than high arousal emotions. Whereas the societal ties between individuals in Western individualistic cultures are somewhat loose, with a focus towards independency, personal identity and self-expression. Consequently, there are relatively fewer restrictions as to how one should behave (Fischer & Manstead, 2000).

Some elements associated with variation across cultures have been explored through the use of display rules. Cultural display rules are socially learned facial cues that govern the conventions for the management of expression in different cultures (Ekman *et al*., 1969). For instance, a study by Friesen (1972) whereby both American and Japanese individuals viewed a stressful film under two conditions. Reported no cultural difference in facial expressions in the absence of the experimenter, supporting universality of emotional expression. However, cultural differences emerged when the film was viewed in the presence of the experimenter, as Japanese volunteer masked negative feelings by smiling. The inhibition of emotion by Japanese participants reflects the Japanese cultural ideology of collectivism; wherein there is a greater need to suppress their emotional reactions, to avoid offense, conflict, and confrontation (Matsumoto, 2007). As such, the use of display rules has to be taken into consideration due to their influence in moderating certain social emotional behaviour.

1.2.4 Gender

Notwithstanding biological differences at a gross, macro level (e.g., height, weight, and external genitalia). It has been proposed that combination of innate predispositions (such as genetics and individual developments) along with socialisation of gender-role consistent behaviours have contributed to gender differences in the expressivity of behaviours (Brody, 1993; Brody & Hall, 1993; Chaplin, 2015).

Gender differences in emotion expressions have been reported for adults, with women tending to show greater emotional expressivity (Kring & Gordon, 1998), and internalise negative emotions. Whereas men tend to have stronger emotional experience (Deng *et al*., 2016), although express greater levels of aggression and anger than women (Archer, 2004; Fischer & Evers, 2011). The expressive behaviours of women are thought to reflect their traditional role as being nurturing and as a caregiver, actions that require the suppression of negative emotions and the simulation of positive emotions which facilitate relationship bonds (Chaplin, 2015). Conversely, men more often adopt masculine display rules, where they tend to downplay their emotions. Moreover, assuming the traditional role as the hunter and protector, sensitive to threat stimuli which evoke anger, fear and other similar emotions (Deng *et al*., 2016).

Biological theorists propose that innate gender differences do occur at birth, however different patterns of expressivity between boys and girls become more apparent with age and maturation in response to interactions with their environments (Chaplin & Aldao, 2013). This is because age, affords experience with and opportunities to conform to male and female gender roles (Buck, 1984). This has been supported by studies that have found no gender effects in facial expressivity occurring in infancy (LoBue & Thrasher, 2015). However, negative emotions become pronounced in boys at toddler/preschool age and positive emotions are more pronounced in girls than in boys during middle childhood and adolescence (Chaplin & Aldao, 2013). This suggests that gender differences are not innate but rather are socialised. This socialisation effect for externalising emotions for gender may be moderated by age.

1.2.5 Age related differences

As emotion is a prominent feature throughout life, there would be expected age-related differences in emotional FE. Aging is a cumulative process of changes in the skin, soft tissues (subcutaneous fat, muscle, and fascia), and skeleton of the face (bone and teeth). Combining the effects of gravity, subcutaneous fat redistribution, decreased tissue elasticity and soft tissue fullness, can give rise to superficial textural wrinkles, folds and sagging of the skin (Coleman & Grover, 2006). Hence, can interfere with the perception of emotion and render the quality of FE more recognisable in younger rather than older people (Fölster *et al*., 2014).

Another aspect of facial behaviour that appears to change with age has to do with affective processing in the brain. Throughout childhood and into adolescence, the brain undergoes significant growth and development from continual thickening of cortical areas and proliferation of neural connection (Johnson *et al*., 2009). In adolescence, fundamental reorganisation of the brain takes place whereby there is an imbalance between the maturing of brain regions associated with production of emotions, and a slower development in brain structures such as the PFC linked with managing them (Del Piero *et al*., 2016). This marks a heightened period of emotional reactivity and affect. The pattern of cognitive control and fine tuning of the neural networks that produce and manage emotions will only improve with maturation of the PFC well into the 20's (Guyer *et al*., 2016).

Accumulated life experience coupled with age-related increases in prefrontal activity and reduced amygdala activity in response to emotional stimuli confers improved emotional regulatory skills. With age and experience, people may be generally less expressive as they learn to attenuate and manage emotional reactions more constructively (Lawton *et al*., 1992; Fölster *et al*., 2014). Moreover, older adults are shown to be less expressive to negative stimuli (Neiss *et al*., 2009) and more responsive towards positive experiences (van Reekum *et al*., 2011). This may be due to two explanations: 1. Having better regulation of emotions means they can more easily defuse negative feelings in situations; 2. Older adults tend to deploy strategies that involve ignoring things that might elicit negative emotion, and hence a natural tendency in favouring positive material to minimise engagement with negative stimuli (Lawton *et al*., 1992; Carstensen *et al*., 2000; Mather, 2012).

1.2.6 Individual Differences

Other factors that may affect variability in observed emotional FE are individual difference factors such as personality, life experiences and social relationships. Personality can be conceptualised in terms of five major traits, often called the Big Five: Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness to Experience (Hampson, 2012). Where each personality dimension represents a range between two extremes e.g., extreme extraversion and extreme introversion.

Certain personality traits have shown to demonstrate dispositional characteristic and may represent specific vulnerabilities to particular affective states (Larsen & Ketelaar, 1989). For example, extraversion/ sociability traits often exhibit heightened reactivity to positive affective states than those of introverts. Negative emotionality is associated with a cluster of primary neurotic traits, such as stress reaction, trait anxiety (Larsen & Ketelaar, 1989; Rafieinia *et al*., 2008). Moreover, people high in neuroticism tend to focus more on threatening stimuli, which may make them prone to negative affect (Matthews *et al*., 2009).

Personal life experience has also played a key role in affective processing, as affective responses are essentially formed through learning and experience (Damasio, 1994). Personal experiences influence the way people interpret situational information, the way they appraise and deal with challenges, and how they learn from them. The emotional outcome will depend on what experiences the person associates with those events from their past. Moreover, since emotional responses and regulation frequently take place in social situations (Gross & John, 2003). It is within social relationship dynamics that people tend to experience the broadest range of emotions (Fitness, 2015). The emotional diversity that develops with personal experience and through relationships can refine the pattern of responses to a broad spectrum of situations.

1.3 Measuring Facial Expressions

The measurement of emotional facial behaviours can be acquired through two main methods: facial electromyography (EMG) (Cacioppo & Petty, 1986; Dimberg, 1990), or visual analysis of facial activity (Buck & Savin, 1972; Ekman *et al*., 1980). The applications for either method is dependent upon theoretical and practical considerations. Assessments from visual analysis of facial activity involve the use of a human dependent observational coding system (Cohn *et al*., 1999). One of the most common and valid observer-based coding methods that has been developed is the Facial Action Coding System (FACS) (Ekman *et al*., 2002).

FACS categorises facial behaviours based on the muscles that produce them. The system catalogues all possible movements the face can produce into forty-four different “action units” (AUs) (see Table 1.3). Thirty of which are related to contraction of specific muscles

(Ekman *et al*., 2002). The AUs code for contractions in facial musculature which can be used either separately or in combination to determine an emotional expression (Tian *et al*., 2001).

Table 1.3: Examples of Action Units (AUs) from the Facial Action Coding System (FACS)

AU number	Name of action	Muscle(s) activated
1	Inner brow raiser	*Frontalis (pars medialis)*
2	Outer brow raiser	*Frontalis (pars lateralis)*
4	Brow lower	*Corrugator supercilii, depressor Supercilii, procerus*
5	Upperlid Raiser	*Levator palpebrae superioris*
6	Cheek raiser	*Orbicularis oculi (pars orbitalis)*
7	Lid tightener	*Orbicularis oculi (pars medialis)*
8	Lips towards each other	*Orbicularis oris*
9	Nose wrinkler	*Levator labii superioris alaeque nasi*
10	Upper lid raiser	*Levator labii superioris*
11	Nasolabial deepener	*Zygomaticus minor*
12	Lip corner puller	*Zygomaticus major*

Table 1.3 illustrates of some of the Action Units from the Facial Action Coding System (FACS). FACS taxonomies human facial movements into Action Units (AUs) that represent the muscular activity that produces *facial* appearance changes. *The coded AU numbers are arbitrary and do not correspond to any significant value. Adapted from Ekman et al. (2002).*

Key: AU = Action Units; FACS = Facial Action Coding System

The FACS method has been shown to accurately predict an emotional experience, specifically when an affective change occurs (Ekman *et al*., 1980). For example, the expression of amusement is described by a combination of the contraction of AU 6 (*orbicularis oculi*) which raises the cheeks and causes wrinkling lateral to the eyes, and AU 12 (*zygomaticus major*) which pulls the lip corners up into a smile. This can be useful in distinguishing between spontaneous Duchenne smiles and simulated ‘controlled’ smiles from the associated activity of AU 6 (Ekman *et al.*, 1990).

Although FACS remains the gold standard research tool for analysis of facial behaviour, the drawbacks of the coding systems for facial movement analysis are that it suffers the common hindrance of being “human-observer dependent, labor intensive, and difficult to standardize.” (Cohn *et al*., 1999). The FACS requires approximately 100 hours of training to identify and interpret data into AUs and one minute of video recording takes one hour to score, this limits suitability for real time analysis. Failing to be automated, is where these systems are greatly confined hence a shift of focus towards to developing automatic systems.

1.3.1 Automatic Facial Expression Analysis

Research efforts in the area of human computer interaction has extended towards developing automatic systems for recognising FE. The prototype system, known as an automatic facial expression recognition (FER) system uses machine learning and pattern recognition techniques for image and video processing. The FER system is defined by its ability to effectively measure and classify expressions of emotion (Chibelushi *et al.*, 2002). An automatic FER system follows three main steps (Figure 1.7) that are similar to other visual biometric techniques such as facial recognition. However, whilst face recognition looks for individual differences FER looks for similarities. The steps involve: face detection, feature extraction, expression classification (Zhang, 1999; Sumathi *et al.*, 2012).

Figure 1.7: Basic structure of Facial Expression Recognition (FER) systems

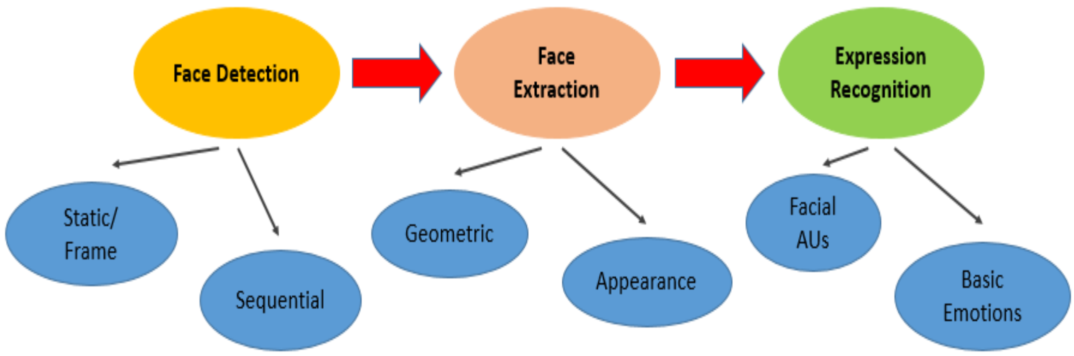


Figure 1.7 displays the basic architecture underlying FER systems. The automatic FE recognition system involves three steps: face detection, feature extraction, and expression recognition. There are a variety of methods available to completing each step, depending on the type of input data. Adapted from Sumathi et al. (2012).

Key: FE = Facial expression; FER = Facial expression recognition

Face detection initiates the processes of FER. An acquisition device such as a camera is used to capture the face within a scene for the input image. The input image/s can either be static – a single image showing the peak FE, or sequential – an image sequence displaying an emotion over time. Pre-processing is often required to scale, rotate, and normalise image intensity to achieve a pure isolate of the face and to eliminate redundant areas (Hemalatha & Sumathi, 2014). Once the face has been detected, the next step is to extract information about the changes in the appearance of facial features.

Feature extraction involves transforming the input data to a reduced set of descriptors which encode relevant information (Youssif & Asker, 2011). There are two mainstream approaches to feature extraction: geometric-based and appearance-based approaches (Zhang, 1999). In geometric-based approaches, smaller regions such as features, and edges are extracted from the images. Appearance-based approaches utilise the whole face and typically extracts data using grayscale pixel motion vectors or sequence responses filters such as Gabor wavelets (Mliki *et al*., 2012).

The extracted relevant information is fed through and processed by a classifier which maps facial feature changes into a category. Expression classification is given by assigning the patterns of movement into either facial AUs, or the basic emotional FE using AU combinations (Pantic & Rothkrantz, 2000).

In FE recognition, feature extraction plays a central role in representing key components of an expression. Good extraction methods should have superior discrimination capability to improve recognition performance (Wang *et al*., 2014). As emotions are displayed over time, motion-based tracking has been an attractive approach to acquire temporal patterning of the facial motion.

Various proposed systems have employed different techniques and methods that are used in combinations for expression analysis. Optical flow-based motion detection methods have been used, including in our studies, to extract dynamic facial movement from image sequences (Mase, 1990; Yacoob & Davis, 1996; Essa & Pentland, 1997; Otsuka, 1997; Sanchez *et al*., 2011; Sidavong *et al*., 2019). This approach extracts motion from the changes in movement patterns of the skin to discriminate facial displays, by measuring displacement of corresponding pixels between successive frames (Cohn *et al*., 1999). The technique is often applied using different algorithm to calculate movement of facial features (Yacoob & Davis, 1996; Essa & Pentland, 1997; Cohn *et al*., 1999). For instance, Uddin and colleagues (2013) combined optical flow techniques with Principal Component Analysis (PCA) and General Discriminant Analysis (GDA) to extract movement activity from facial expression image sequences from the Cohn-Kanade facial expression database (Cohn *et al.*, 1999). The feature extraction method provided the system with an average recognition rate of 99.16% for the expressions of anger, joy, sadness, surprise, fear and disgust (Uddin *et al.*, 2013). Yacoob and Davis (1996) implemented an optical flow algorithm to track the motion of the facial features across a large set of image sequences of volitional expressions displayed by subjects. They were able to distinguish between six basic facial expressions of emotions.

1.3.2 Optical Flow Technique

Optical flow is defined as an apparent motion of image brightness (Abdat *et al.*, 2010). For expression recognition, optical flow methods try to calculate the motion between moving objects relative to the sensor. The motion is depicted along two image frames that are taken between times t and t + δt (change in time) at every pixel position (Figure 1.8).

Figure 1.8: Pixel movement between two image frames

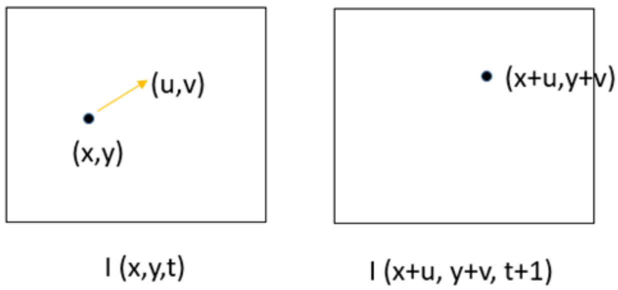


Figure 1.8 illustrates the movement of a pixel between two image sequences. Where I (x, y, t) is the intensity of a pixel (x, y) at time t and the flow is (u, v) at time t+1.

The differential methods of optical flow are based on local Taylor series approximations (Psaltis, 2013) given the assumptions of brightness constancy (Sanchez *et al.*, 2011) which infer that pixel intensities of an object are conserved from one frame to the next (Fleet & Weiss, 2006). As such this yields optic flow constraint equation $I_x u + I_y v + I_t = 0$, where the subscripts denote the partial derivatives of the image I, and (u, v) are the displacement of the pixel or image intensity between the two frames.

However, a problem arises as the single equation expresses one constraint on two unknowns u and v for a single pixel and thus cannot be solved. The inadequacy of the optical flow formula for calculating motion is a mathematical consequence of the aperture problem (Figure 1.9), where there is insufficient information within the small area to uniquely determine motion.

Figure 1.9: The Aperture Problem

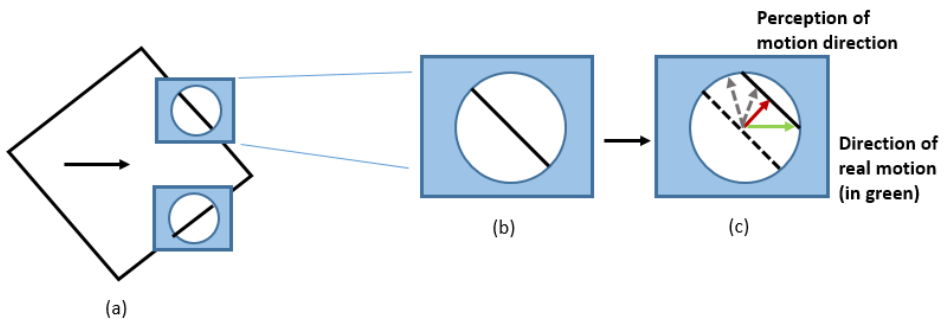


Figure 1.9 describes the ambiguity of perceiving the motion of an object through a local observation. Where in (a) the edge of an object can be seen in the aperture. (B) is a close up view of the object edge through the aperture before motion and (c) view of the object's edge through the aperture after motion. Thus, giving the flow component perpendicular to the edge line as depicted by the red arrow is perceived as the most likely solution when the actual motion is depicted in green. Adapted from Murakami (2004).

1.3.2.1 Lucas Kanade Optical Flow

The Lucas-Kanade (1981) method has been used to overcome the aperture problem by making a smoothness assumption, that for much of the image, all pixels will move similarly to their neighbours (Patel & Upadhyay, 2013; Psaltis, 2013). As such the algorithm solves the basic optical flow equations for all the pixels in a small e.g., 3 x 3 patch/ local neighbourhood, by the least squares criterion (Rojas, 2013). The Lucas-Kanade (LK) algorithm is used as the basis for optical flow analysis because of its excellence in calculating speeds and accurate time derivatives. The limitations of this algorithm are that it does not provide confident boundaries around the movement of objects which may need to be reviewed (Patel & Upadhyay, 2013).

1.3.3 Facial Landmarks Analysis

Facial landmark analysis is relatively new for emotional expression analysis (Bailenson *et al*., 2008; Gopalan *et al*., 2018; Khan, 2018). The method involves the detection of facial landmarks or salient points on the face, to which the spatial configuration and temporal dynamics of the landmarks are measured and used to describe facial expressions (Çeliktutan *et al*., 2013; Ouanan *et al*., 2016).

Facial landmarks are generally classified into two groups: as fiducial/ primary and ancillary/ secondary. Fiducial points are located around edges and corners of facial components such as the eyebrows, eyes, nose, and mouth. These points are usually easily detected hence considered primary (Çeliktutan *et al*., 2013). Ancillary (secondary) facial landmarks make-up the contours, and outlines of facial features, these are determined using spatial information of these fiducial landmarks. The primary and secondary landmarks commonly reported in the literature are the m17 landmark set that consists of 17 inner landmark points within the face contour (2 each for the eyebrows, 3 each for the eyes, 3 for the nose and 4 feature points for the mouth) (Çeliktutan *et al*., 2013).

In general, the Euclidean distance between landmarks is used as a morphometric measure. Once facial feature points are obtained from a facial image, pairs of landmarks are selected, and the corresponding angles and Euclidean distances are computed. The information is then used to generate feature vectors for expression classification (Khan, 2018).

In video sequences, many systems (Akakin & Sankur, 2011; Ghimire & Lee, 2013; Suk & Prabhakaran, 2014) measure the geometrical displacement of facial landmarks between the current frame and previous frame as temporal features. Suk and Prabhakaran (2014) proposed a real time emotion recognition system which integrated Haar cascade facial detection and the Active Shape Model (ASM) onto a face. Dynamic features were generated by the displacement between neutral and expression features and used as an input for Support Vector Machine (SVM) classifiers. The system achieved an average recognition rate of 72% for seven expressions, performing well in the recognition of happiness at 98% and surprise at 91% but poorly with sadness, fear and anger yielding an average 43% recognition accuracy. One of the reasons for low accuracy in negative emotions was due to human error in performance of emotional expressions. These subjects were unclear as how to act out certain emotional expressions that were not felt which contributed to variability of expressions captured.

The accuracy requirements and number of landmark points vary between applications. For example, Khan (2018) used an Intraface 49-point facial landmark detector as Sobel filters and Shi Tomasi edge and corner detections methods to extract 49 feature points of eyebrows, eyes, nose, and lips to achieve 84-98% recognition accuracy between the basic emotional FE. Besinger *et al.* (2010) also used a feature point tracking algorithm that was separately applied to five facial image regions of the eyebrows, eyes and mouth to a total of 26 landmarks achieving an overall detection accuracy of 63.33%. Their approach utilised a mixture of database image sequences from Kamachi *et al.* (1998), Kanade *et al.* (2000), Liu (2002) and Duthoit *et al.* (2008). Day (2016) achieved 47% accuracy using 68 landmark points and whilst other studies have used as little as 20 (Hassan & Mohammed, 2020) or 26 (Tie & Guan, 2013) landmark points on the facial region to facilitate expression analysis.

Though the concept of facial landmark analysis seems simple, automated landmark tracking still presents a challenge for computer vision as surface deformations of the face from expressions under vary lighting conditions and occlusions can cause significant changes to the configuration of tracked landmarks. Resulting in a tendency of the tracker to lose landmark points in subsequent frames (Akakin & Sankur, 2011).

1.4 Gap in research

Despite significant development in computer vision technology, recognition of emotional facial expressions by a computer remains a challenge (Chibelushi *et al*., 2002). Most of the existing studies limit FE recognition to full frontal facial analysis (Fischer, 2004). Very few studies having addressed recognition in the presence of occlusion (Kotsia *et al*., 2008; Ekenel & Stiefelhagen, 2009). A study by Kotsia *et al*. (2008) showed that eye occlusion affects the recognition of the emotions of disgust and surprise, while occlusions to the lower half of the face affected the recognition of anger, happiness, and sadness. Interestingly, occlusions to the left/ right facial region did not affect recognition accuracy rate, indicating that both facial regions possess similar discriminatory information. Systems amended to real world applications like surveillance purposes should allow for faces to be reliably decoded at a variety of angles not limited to full features of the whole face, which may not be continuously available on camera. In reality, out of plane variation of head position is common and often accompanies change in expression (Kanade *et al*., 2000).

Another drawback on the performance of standard automatic FER system is failure to detect and classify naturally occurring expressions which limits its applications. Many automatic FER systems have favoured for their set-up, the use of posed emotional facial expressions (such as those expressed under voluntary control) to train systems due the ease of elicitation in controlled laboratory conditions (Hammal *et al.*, 2007) and availability of databases for those images. The common facial expression databases most often used to train systems are the Man-Machine Interaction (MMI) (Pantic *et al*., 2005), Cohn-Kanade (CK+) (Kanade *et al*., 2000) and the Japanese Female Facial Expression (JAFFE) (Lyons *et al*., 1999) databases. Most databases are composed of posed or deliberate expressions which emerge from request demands.

With the induction of posed expressions, the facial behaviours appear more intense and well defined due to clear intention to convey the targeted emotion. Laboratory FER achieves very high accuracy (up to 97%) due to exaggeration of facial features (Samadiani *et al.*, 2019). This may limit the sensitivity range of appearance changes when expected to readily perform on real-life affect expressions where intrinsic (age, gender, ethnicity) and extrinsic (facial hair or other occlusions, head rotations and speech-related facial deformations) factors account for large appearance changes of human faces (Chibelushi *et al*., 2002). Given that subtle expressions occur more frequently, these approaches may fall short in generalising real-world behaviour. Researchers have begun to study spontaneous facial expressions by attempting to induce authentic emotions to acquire more realistic samples (Sebe *et al*., 2006).

The use of photographs, film clips or music to induce emotion have been very successful (Kucera & Haviger, 2012). Pictures and sounds have been used more frequently in psychological research because of the presence of established and standardised databases such as the International Affective Pictures System (IAPS) (Lang *et al*., 2005).

In a typical picture induction study, participants are shown a series of images, and asked to rate their own emotion. The benefits of using images as an induction stimulus is that they are normalised for affect in discrete emotions (Mikels *et al*., 2005; Libkuman *et al*., 2007).

Film stimuli have the ability to induce emotions for longer periods of time at both subjective and physiological levels (Rottenberg *et al*., 2007; Carvalho *et al*., 2012). The purpose of film is to use conceptual knowledge to evoke prior experience, this is important for creating emotional states from simple affective changes (Barrett & Bliss-Moreau, 2009). For example, the final scene from the film The Champ (1979) directed by Franco Zeffirelli, shows a boy named "T.J." witness his father's death long after his win in a comeback fight. The clip allows the viewer to see both the boy's emotion of sadness and pain of losing a loved one. The use of sound and dialogue increases the potency of the stimulation and conveys emotional information in a way that static images cannot achieve (Howard, 2014).

Films have a relatively high degree of ecological validity as the emotion-inducing matter utilises both dynamic visual and auditory stimuli to great effect. This makes film stimuli more desirable however a limitation of film use is that there are no widely accepted and validated set of emotion-eliciting film stimuli (Kennedy-Moore & Watson, 1999).

1.5 Current Research at the University of Technology, Sydney (UTS)

The University of Technology, Sydney (UTS) Predictive Facial Imaging Unit has explored the use of optical flow technique to extract feature information from emotional facial responses. The research group has employed the use of short film clips to instigate natural emotional responses from subjects who were recorded on video. Duthoit (2007) initiated the investigation into the recognition of emotions from FE using optical flow. The study was unsuccessful in producing a computational algorithm for emotional analysis having used a small sample size (N=8). The validity of the FE database produced was questioned by Besinger *et al*. (2010) as to whether the expressions were natural or forced mimicry. Valiant efforts have gone into refining experimental procedures to authenticate and produce greater sample sizes to assess three emotional states: sadness, amusement, and fear.

The research team has extended the works by exploring various facial features (Chow, 2010; Kilincer, 2011), the use of feature point tracking (Besinger *et al*., 2010), intensity variations between factors such as sex, age (Llave, 2011; Nguyen, 2014), and culture (Siwan, 2015). Changes in physiological responses were also assessed by measuring Electrodermal Activity (EDA) (Siwan, 2015) to validate captured emotions.

Studies concerning mental states and emotions (Nakasone *et al*., 2005) have successfully used EDA as a physiological measurement of emotional arousal (van Dooren *et al*., 2012; Valenza *et al*., 2014). EDA refers to the varying electrical properties of the skin in response to eccrine sweat gland activity. The eccrine sweat glands are controlled by the sympathetic branch of the autonomic nervous system (Figner & Murphy, 2011; van Dooren *et al*., 2012) which are influenced by the higher subcortical (hippocampus, basal ganglia amygdala) and cortical areas (PFC). These areas form part of the limbic and paralimbic networks which are involved in affective and emotional processes. Therefore, modulation of the body's arousal in response to the presentation of an emotional stimulus can be observed in EDA patterns (Figner & Murphy, 2011; Schupak, 2014). Despite the developments, studies have failed to establish classification framework for emotions due to time constraints of the aforementioned studies.

1.6 Research Objectives

The objectives of this research were to extract motion activity from facial expressions of emotion. The study involved the use of short films to induce different emotional states in individuals which were recorded onto video footage. Facial images were extracted from those video recordings and two different methods of analysis of facial activity implemented and compared: LK optical flow and facial landmark analysis. As this was an exploratory study, the investigation has been kept to the simplest expressions that could be easily elicited across three emotional states: amusement, sadness, and fear.

Based on the current understanding of the universality of emotional FE (Ekman, 2003), this research investigated as to whether the side of the face retains discriminative information for FE recognition. Profile images may benefit FE recognition given the likelihoods of situations where there is reduced visibility of the face. More often than not the occurrence of situations where parts of the face are obscured by an object or, as a result of a person moving their head, not all features of the face will be seen on camera. If the use of a portion of the face yields similar thresholds for detection, then the ability to discern emotional FE using a reduce set of features will decrease processing time and the errors rate for the incorrect recognition of expression.

In this study, images of FE collected were cropped manually to extract facial motion for subsequent analysis classification of emotional expressions. This work is vulnerable to potential experimental demand effects such as the exaggeration or inhibition of expressions while experiencing stimuli. Equally verbal and paper and pencil measures were limited in their ability to assess emotional responses. The presented study also recorded EDA patterns as a physiological measure to authenticate the presence of emotion. However, it is important to note that physiological measurements reflecting autonomic nervous system activity are incomplete as gauges of emotion (G & R Cooperatives, 2013), as they mostly reflect arousal. Thus, it was used only as a validation tool to supplement self-reporting of the recorded emotions.

1.7 Hypotheses & Aims

Hypotheses:

It was hypothesised that:

1. The use of short film clips would induce facial expressions of discrete emotional states.
2. Coordination between expressive behaviour, and physiological responses would improve the reliability and precision of the elicited emotion facial expressions.
3. The patterns of facial expressions of emotions are unique and can be differentiated and classified from the frontal, profile left and profile right facial orientations.

Aims:

1. To induce naturally occurring emotions: amusement, sadness and fear in individuals.
2. Validate the instigated emotions as revealed through FE using self-reports and Electrodermal activity (EDA)/ Skin conductance (SC) analysis.
3. To classify and interpret facial activity data from the frontal and left and right profile facial orientations.

Chapter 2 – Research Design, Methodology, & Statistical Analysis

2.1 Subject Recruitment

A total of 142 participants (males = 50, females = 92) were recruited from the local Sydney population to take part in the emotion induction experiment. The participants ranged in age from 18-34 years. Method of recruitment included posters, flyers, announcements, email and UTS staff notices, and existing personal contacts. A website was also created to increase social media status and comprehensive information about the study.

2.2 Ethics approval

This study received ethics approval from the UTS Human Research Ethics Committee (HREC) (HREC: 2014000110).

2.3 Selection criteria

The suitability of the volunteers for the current study was determined by a Lifestyle Appraisal Questionnaire (LAQ) (Craig *et al.*, 1996), as well as a personal demographics form. Participation in this current research required the following inclusion/ exclusion criteria:

i. Subjects were not permitted to be under the influence of any drugs, alcohol, medication, or suffering from an ongoing chronic disease or illness. This was determined by the responses to Questions 8 and 18 of the (LAQ); "*Q8. DO you take any drugs or medication?", "Q18: Do you, at present, suffer from any chronic disease or illness?*" (Craig *et al.*, 1996).

ii. Subjects were required to have their blood pressure readings taken at the beginning, during and at the end of the study. The subject must have had a resting systolic blood pressure of less than 160 mmHg, and diastolic reading of less than 100 mmHg.

iii. Participants were aged between 18 to 34 years and proficient in spoken and written English to avoid any possible misunderstanding with regards to the content of the films and questionnaires.

If any of these selection criteria were not met, the volunteer was excluded from the study, as per the HREC approved protocol.
The following section describes the two experimental protocols (a) and (b) used in this research.

2.4 Sample size

The sample size (n) refers to the number of participants or observations in a study. It is one element of the research design that influences the reliability or precision of the results and the power of the study to draw conclusions (Cohen, 1977; Institute for Work & Health [IWH], 2008). The power of a study is defined as 1 - the probability of Type II error (Biau *et al.,* 2008). Where the Type II error is the acceptance of a null hypothesis, concluding there is not a significant effect, when in fact there was. Hence, the power of a study reflects the probability of detecting a difference when this difference exists. Increasing the sample size increases the power to detect differences, however, using too many participants in a study is expensive and exposes participants to unnecessary further investigation after appropriate conclusions should have been reached (Biau *et al*., 2008). Therefore, it is important that studies are planned with adequate sample size in mind to give enough power to detect a statistically significant difference if a difference truly exist (Biau *et al*., 2008; Burmeister & Aitken, 2012).

The sample size estimations for this study were based on a study by Cohen (1992) who demonstrated that the minimum sample size required for the analysis conducted with a sample power = 0.80 and moderate to large effect size (Cohen's *d* of 0.5- 0.8), meaning that is a large enough observable effect between sample means, is approximately 30 samplings. This study aimed to recruit a population sample of at least 30 people to obtain adequate number of facial images of each emotion expression class.

Previous research conducted within the unit (Chow, 2010; Llave, 2011; Nguyen, 2014; Siwan, 2015; Chow *et al*., 2019) have utilised smaller sample sizes to the ones presented in the current thesis. On the other hand, published studies on emotion elicitation (Gross & Levenson, 1995; Howard, 2014; Uhrig *et al.*, 2016), and emotional facial expressions (Cohn *et al*., 1999; Besinger *et al*., 2010; Khan, 2018) have varied in sample sizes ranging from approximately n=60 to n=494 for some of the test groups in the studies listed. This is also dependent as to whether researchers recruited subjects for the study or the use of data from existing databases.

2.5 Experimental protocol (a)

Protocol (a) refers to the induction of emotions.

2.5.1 Experimental design

The study was conducted in a 4 x 3 m recording space with a table centred at one end of the wall. On the table were: the EDA equipment, blood pressure monitor (OMRON HEM-7221, Japan), desktop speakers (Philips BT4080B, Netherlands) and a viewing screen (LG 22M37D, South Korea) attached to a freely rotatable monitor arm (Silverstone ARM11SC, Taiwan). An adjacent room to the filming space was used as a monitoring area for the investigator to externally view and monitor the session. This deliberate separation of the two areas between the volunteer and the researcher was to minimise the Hawthorne Effect (Coombs & Smith, 2003), which refers to the tendency of individuals to modify their behaviour in the presence of others.

Three video cameras (Canon Legria HFM31 HD, Japan) labelled 1, 2 and 3 were positioned 1.0m away from the participant (Figure 2.1). Camera 1 was fixed on a tripod (Sirix MAX3512, Australia) behind the viewing monitor. Cameras 2 and 3 were fixed on tripods (Silk F630, Japan), to the left and right of the participant at an angle of 90 degrees to the frontal view. All camera lenses were directed towards the participant. No zoom was used for the recording, and height of the cameras was adjusted accordingly to each participant's stature to capture their headshots. Two light diffusers were positioned at either side of the room to create even lighting. The position of the legs of the chair on which the subject was seated, the tripods and diffusers were marked on the ground using coloured tape to ensure standardised recording for all participants throughout the investigation.

Figure 2.1: Experimental set-up

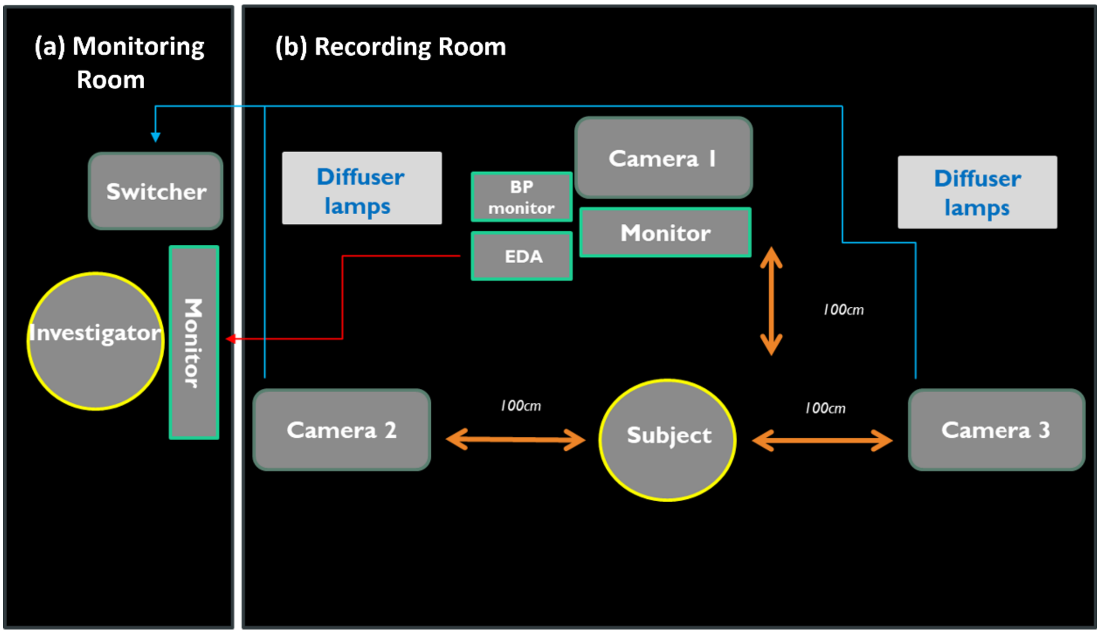


Figure 2.1 displays the basic design of the filming room. The filming room consists of (a) monitoring room which receives output recordings from the electrodermal and video recording equipment from the recording room` (b) where the subject was seated whilst viewing short films. The blue arrow indicated the cables connecting the cameras to the switcher and the red arrow denoted the connection cable between the EDA equipment and monitor.

Key: BP = Blood Pressure; EDA = Electrodermal Activity

2.5.2 Materials and Equipment

A full list of equipment that was used in the study is outlined in Table 2.1. This includes the software and programs used to record and analyse data. Furthermore, information pertaining to the make and model as well as the function of each item.

Table 2.1: Equipment List

	Brand/Developer	Model/Version	Details
3	Canon (Japan)	Legria HFM31 HD	Digital video camera
2	SLIK (Japan)	F630	Video camera tripod
1	MAXXUM (AUS)	Sirix MAX3512	Video camera tripod
2	Shuangyang (China)	5070	Light diffusers
1	Philips (Netherlands)	BT4080B	Speakers
1	Dell (USA)	Optiplex 780	Desktop computer
1	Dell (USA)	1708FPt	Computer monitor
1	SilverStone (Taiwan)	ARM11SC	Freely Rotatable Monitor Arm
1	AV Digitech (AUS)	AC-1708	HDMI Switcher
1	LG (South Korea)	22M37D	Computer Monitor
1	Life Technologies Inc. (USA)	Procomp 5 Infiniti	Electro-dermal response equipment and software
1	Thought Technology Ltd. (Canada)	SC-Flex/Pro SA9309	Electro-dermal response electrodes
1	Omron (Japan)	HEM-7221	Automatic blood pressure monitor
1	MATHWORKS (USA)	MATrice LABoratory (MATLAB) 9.3, R2017b edition	Programming platform for analysis Licence: UTS
1	Microsoft (USA)	Windows 10	Operating system for desktop computer Licence: UTS
1	Microsoft (USA)	Microsoft office 2013 (Word, Excel)	Software used in analysis Licence: UTS
1	Adobe (USA)	Adobe Creative Cloud Suite (CC)	Video editing software Licence: UTS
1	Adobe (USA)	Premiere Elements 13	Video editing software Licence: Private
1	IBM (USA)	SPSS Statistics 19	Software used in statistical analysis Licence: UTS

Table 2.1 highlights all equipment used in the study. The information includes additional details such as quantity, brand and model.

2.5.3 Induction Stimulus of Emotional Response

This study aimed to evoke three emotional responses: amusement, sadness, and fear. The use of film clips allowed the presentation of more evocative and complex stimuli in a short amount of time (Howard, 2014). A study conducted by Philippot (1993) to evoke emotion using film stimuli reported success in eliciting the emotions: amusement and sadness. But had less success in eliciting anger, disgust, and fear. Philippot (1993) used a small ethnically homogenous sample with 3 different self-report procedures. Gross and Levenson (1995) adopted a more objective criterion for selection of films using only the intensity and discreteness of the elicited response. They were able to increase the pool of films and diversity of subjects with a single self-report method.

This study adopted Gross and Levenson (1995) criteria to select films aimed to elicit the targeted emotions: amusement, sadness, and fear. The chosen film clips were based on measure of valence (pleasantness), arousal (intensity), and discreteness of the emotion elicited used in film validation studies (Gross & Levenson, 1995; Bartlett *et al.,* 1999; Schaefer *et al.*, 2010).

2.5.4 Selection of Emotional Film Stimulus

Despite having a relatively high degree of ecological validity, it was important to possess an adequate set of stimuli which, under ordinary circumstances, reliably elicit particular emotions in subjects. The choice of film stimulus was based on its ability with ease to convey meaning to a wide audience.

A large number of short films, sketches, and commercials were sourced from various online websites (such as Youtube, Vimeo, and ShortsoftheWeek). The clips viewed were ones that were considered relevant for the needs of the study and based on their ability to appeal to a greater audience in terms of relevance to a contemporary context. From a corpus of 80 short clips that were viewed, 8 were selected for additional evaluation with regards to which emotions they would elicit most strongly. After careful consideration, the 8-clip selection was reduced to 3, one for each emotion. The films ranged from 2-5 minutes. The films chosen to evoke amusement, sadness and fear respectively were: "*Never Say No to Panda*" (2010) created by Advantage Marketing and Advertising company, "*Last Minutes with Oden*" (Directed by Eliot Rausch, 2009) and

"*Lights Out*" (Directed by David F. Sandberg, 2013). The "*Never Say No to Panda*" clips (2010) were acquired from the Advantage Marketing and Advertising agency website. "*Last Minutes with Oden*" (2009) and "*Lights Out*" (2013) were obtained from the directors Vimeo Webpage after being granted copyright use by the directors.

The "*Never say no to Panda*" is a short clip comprising a series of four commercials, the first three ads follow the same formula: and individual for one reason or another declines the offer of Panda cheese, a giant panda mascot shows up and goes on destructive but hilarious rampage whilst the Buddy Holly song "True Love Ways" plays in the background. It is only in the last ad when the cheese is accepted, that all parties walk away peacefully (duration: 180 seconds). The short documentary "*Last Minutes with Oden*" entails the special friendship between the two main characters, Jason and his dog Oden, and features a voice over narrative. The story beings and ends with Jason riding his bike in the rain, recollecting the day he put down his dog to end its pain and suffering from cancer. At the vet, Jason starts to tear up whilst saying goodbye to Oden, as he is comforted by the nurse (duration: 270 seconds). Lastly, "*Lights Out*" is a horror short film that contains a narrative without dialogue: in it, a silhouette appears in the hallway of a woman's apartment when she turns off the lights; scared, the woman keeps the lamp on and huddles under a blanket cover. She begins to hear footsteps in the hallway, followed by persistent flickering of light from the lamp, when she uncovers her head, the figure appears in front of her as the lights go out, ending the film (duration: 160 seconds).

The short films were compiled together into a single film clip, using a fully licensed version of 'Premiere Elements 13' software by Adobe (USA). Each film was preceded by a blank screen, followed by a 5 second countdown and then a Society of Motion Picture and Television Engineers (SMPTE) colour bar image for 10 seconds. This was done for two reasons: 1. To synchronise video recordings; 2. To indicate to the subjects the commencement of a film.

To avoid sequence effects of experienced emotion (Ebbinghaus, 1913), additional film clips were generated, with each of the films arranged in different order of play. This resulted in six predetermined video sequences:

1. Never say no to Panda, Last Minutes with Oden, Lights Out

2. Last Minutes with Oden, Lights Out, Never say no to Panda
3. Lights Out, Never say no to Panda, Last Minutes with Oden
4. Never say no to Panda, Lights Out, Last Minutes with Oden
5. Last Minutes with Oden, Never say no to Panda, Lights Out
6. Lights Out, Last Minutes with Oden, Never say no to Panda

2.5.5 Overview of experimental protocol

Each study was conducted over a single session spanning 30 to 40 minutes. Prior to the commencement of the investigation, the sequence of arranged films to be played was determined by rolling a die. Each number on the die represented a pre-determined order corresponding to the sequence number for the films to be displayed.

Upon arrival, the volunteer was asked to sign a Research Consent Form indicating their permission for the researcher to use and store data for this study and other future projects. They were also informed that all information would be treated as confidential and that they had the ability to withdraw from the study at any time.

The LAQ was administered to determine demographic information and the lifestyle factors of the subject such as mental stability, smoking, alcohol consumption and everyday stressors (Craig *et al.*, 1996). Additionally, a separate HREC approved personal demographics questionnaire was completed to gather specific details about the age, gender and ethnicity/parental ancestry of the participant as well as a pre-study fatigue questionnaire detailing the individual's tiredness level.

A pre- and post-study average blood pressure was measured. The participants were required to rest for 5 minutes before blood pressure measurements were taken using a standard and reliable digital blood pressure monitor [OMRON HEM-7221]. As blood pressure is not always constant (Naring & Staak, 1995), three measurements were taken, and then averaged to ensure consistency and eligibility for the study. A two-minute rest period was also given between each reading to avoid potential carry-over effects from the previous arm cuff compression (Yasuda *et al.*, 2010) and to avoid discomfort to the participant. The three readings were then averaged to produce a single reading.

It was prescribed by the HREC protocol that if at any time during the experimental procedure, should a subject's blood pressure exceed 160/100MmHg, the subject be withdrawn from the experiment and medical assistance sought. If the blood pressure reading was less than 160/100MmHg, but greater than 140/100MmHg, the subject would be advised to consult a medical professional, however, they were given the choice to continue or withdraw from the study.

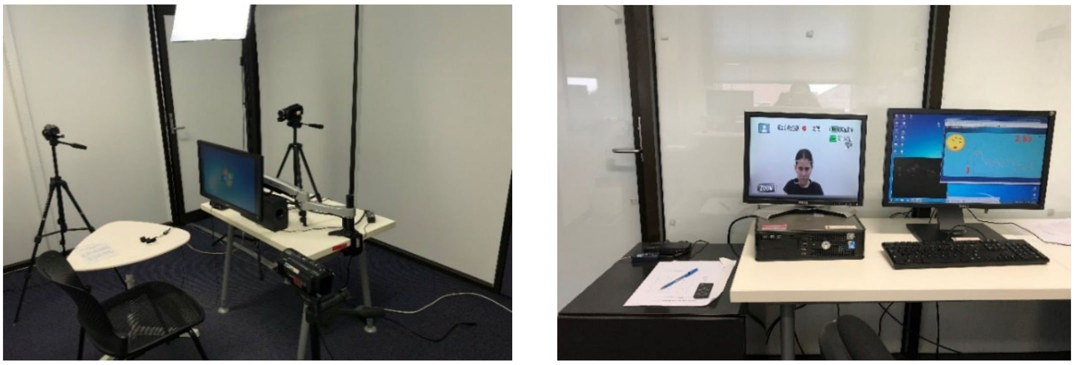
The subject was directed towards the filming area (Figure 2.2a) and seated in front of a 22-inch (53.34cm) computer display monitor (LG 22M37D). The monitor displaying the films was adjusted with the monitor arm to accommodate the volunteer's height and viewing needs.

Two small electrodes were strapped onto the index and middle finger of their non-dominant hand to assess the skin conductance (electrodermal response). This was monitored by the Bio Infinity software and encoder (Thought Technology Ltd, Canada, SA7900, version 6.0.2).

Participants were told that they will be watching a total of 3 short films, though not consecutively, that after each film they would be given a questionnaire to fill. The participant was asked to remove any facial occlusions such as spectacles and for those items to be kept off during the viewing of the films. Participants were informed that prior to each film, a blank screen followed by a 5 second countdown timer and a small test screen pattern for 10 seconds would appear prompting the commencement of the film, at this time they were encouraged to clear their minds of all thoughts. Subjects were told that for the duration of the film screening that it was preferable they try to minimise body movements as best as possible. However, they could avert or shut their eyes if they found the scenes too distressing.

After the subject was seated in a comfortable position. The heights of the cameras were calibrated to centre the subjects face in the recording screen, by adjusting tripod heights. After calibration, the cameras were initiated to being recording and the researcher exited the room to monitor the study in the adjacent room (see Figure 2.2b).

Figure 2.2: Filming and monitoring rooms



(a) Recording Area (b) Monitoring Area

Figure 2.2 displays the images of the experimental set-up of the recording area (a) where the emotional stimuli were viewed, illustrating the placement of the three cameras, lights with diffuser and screening monitor (b) the monitoring area. Permission granted for use of this image.

The subjects were shown a predetermined sequence of 3 short films. While viewing the three clips, the participant's emotional facial response was recorded with all three cameras and observed externally on a monitor [Dell 1708FPt] connected to Camera 1 during the session.

After each short film, the sequence was paused, and the subjects blood pressure was taken to ensure the volunteers wellbeing as required by HREC guidelines. They were given a 16-item emotion self-report questionnaire (see Appendices) to complete and check whether a variety of different emotions were induced. The questionnaire describes 3-4 specific scenes in the short films for example, in Never Say No to Panda (2010) "Panda kicks the spilt groceries and then proceeds to jump on them." The participant was directed to circle the number on the scale: "That number that best describes the intensity felt for each emotion, if you felt any at the specific scene in the film clip you have just seen. On the scale, 0 means you did not feel that emotion and 8 is the most you have ever felt." (Gross & Levenson, 1995).

After completing the scale, subjects were asked whether they had previously seen the film. This cycle was repeated as play resumed for each clip within the sequence. At the conclusion of study, the subject was then led back into the researcher/ monitoring area and asked to complete the post-study fatigue survey and were given a copy of their consent form. An overview of the complete experimental protocol is outlined in Figure 2.3.

Figure 2.3: Flow chart of experimental protocol

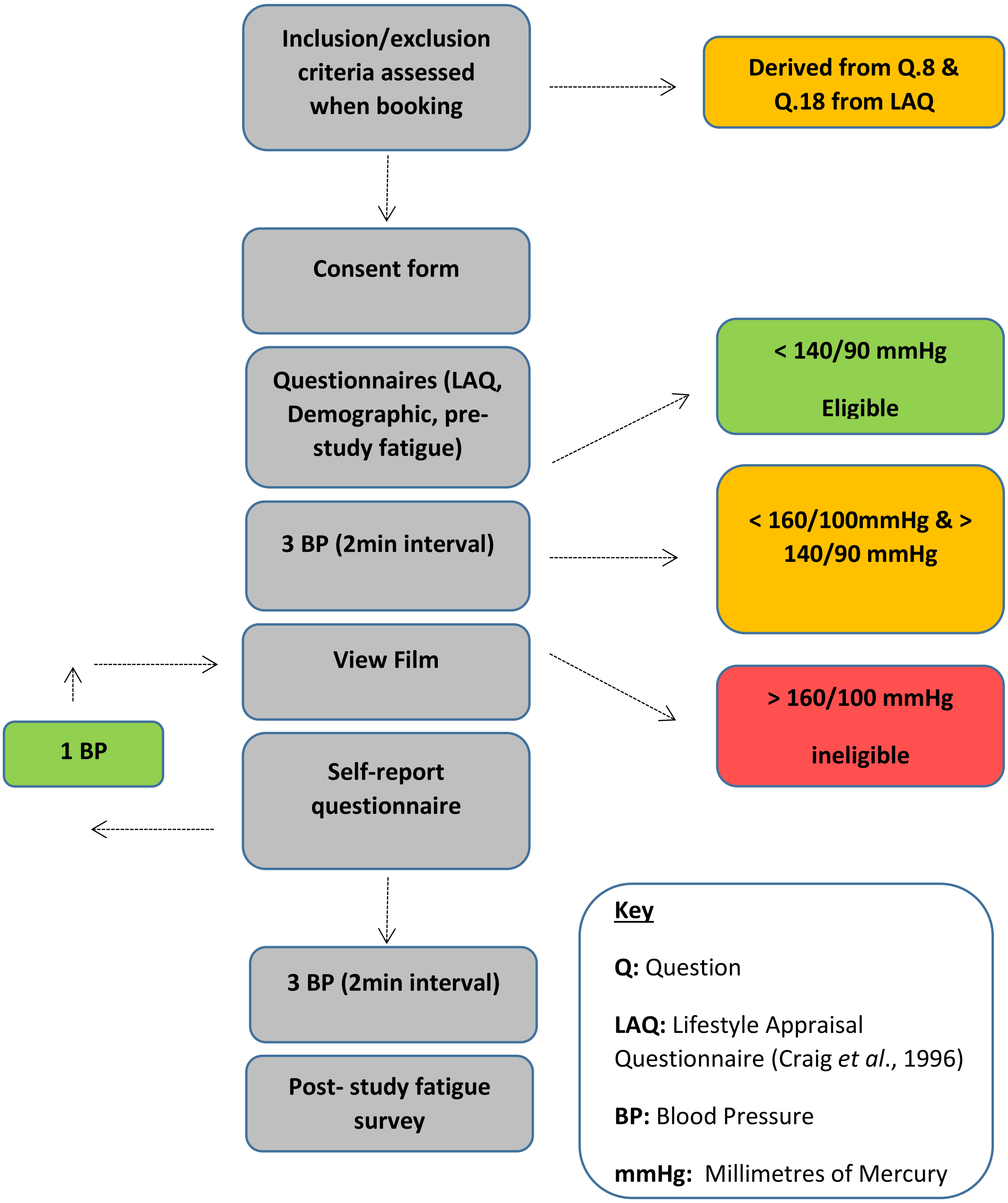


Figure 2.3 displays a flow chart that summaries the experimental protocol that was followed during the study.

2.6 Assessment of Emotional Experience

The study proposed to investigate natural motions of facial activity, as such dynamic facial expressions were the most ideal for analysis because natural facial expressions are sequential in nature (Trautmann *et al.*, 2009). Considering the numerous difficulties related to the elicitation, timing and measurement of dynamic facial expressions of emotion (Rosenberg & Ekman, 1994), it was seen to be appropriate to record video of the facial responses so as to capture the full series of facial movements.

2.6.1 Self-Report Questionnaire

Using emotion for behavioural studies is dependent on knowing the intensity of emotional arousal (Gross & Levenson, 1995). Some researchers favour the use of a Likert-type scale self-reports for emotional evaluation that are explicitly anchored to an absolute set of comparisons (Bartoshuk, 2000).

The aim of the questionnaire was to measure the volunteer's subjective experience of emotion during specific film clips. The reported grading of the emotional experience could then be matched to the facial response within the recorded footage. Izard's Differential Emotions Scales (DES) which aimed to evaluate six emotional states on a five-point Likert scale of 0 (not at all) to 4 (extremely) has been used and validated (Philippot, 1993). Whilst the Five-point DES has potential for use, the method has been scrutinised for being too narrow, and lacking in a wide range of adjectival descriptions to accurately depict discrete qualitative emotional states (Boyle, 1984).

Gross and Levenson (1995) developed a nine-point Likert scale across 16 emotional states: amusement, anger, arousal, confusion, contempt, contentment, disgust, embarrassment, fear, happiness, interest, pain, relief, sadness, surprise, and tension. (Figure 2.4). According to the manual, the intensity rating values are arranged in a Likert scale fashion from 0-8 with 8 representing the highest rating and 0 the lowest rating.

Figure 2.4: Self-report questionnaire

Amusement	0	1	2	3	4	5	6	7	8
Anger	0	1	2	3	4	5	6	7	8
Arousal	0	1	2	3	4	5	6	7	8
Confusion	0	1	2	3	4	5	6	7	8
Contempt	0	1	2	3	4	5	6	7	8
Contentment	0	1	2	3	4	5	6	7	8
Disgust	0	1	2	3	4	5	6	7	8
Embarrassment	0	1	2	3	4	5	6	7	8
Fear	0	1	2	3	4	5	6	7	8
Happiness	0	1	2	3	4	5	6	7	8
Interest	0	1	2	3	4	5	6	7	8
Pain	0	1	2	3	4	5	6	7	8
Relief	0	1	2	3	4	5	6	7	8

Figure 2.4 is an illustration of the Nine-point Likert scale questionnaire used in the study. The nine-point Likert Scale is a self-report questionnaire assessing 16 emotional states with an intensity level on scale from 0 indicating no emotions felt to 8 indicating the highest intensity felt. Adapted from Gross and Levenson (1995).

The study adopted the Gross and Levenson (1995) nine-point Likert scale to measure the intensity of the participant's emotive states for preselected scenes from each of the 3 emotion inducing film clips. For each scene description, volunteers were instructed to:

- Rate the intensity of any one or more of the emotion/s listed on the questionnaire that were felt by circling the number corresponding to that emotion category. The scaling system runs from 0-8 where 0 represents no emotion felt and 8 is the highest intensity of emotion.
- Each question relates to certain scenes from the film shorts.

- If no emotions were felt or were not specified as a category on the questionnaire, please leave it blank.
- More than one emotion can be chosen if multiple emotions were felt.

2.6.2 Electrodermal Activity (EDA) / Skin Conductance (SC)

EDA is frequently used because it is cost-effective, reliable and a non-invasive psychophysiological measurement of emotional arousal (van Dooren *et al.*, 2012). The participant's Electrodermal Activity (EDA) was recorded for a duration of the viewing of the amusement, sadness and fear inducing film clips. The Procomp5 Infinity encoder with the BioGraph infiniti software (Thought Technology Ltd, Canada, SA7900, version 6.0.2) recorded the subject's EDA readings (µS) by encoding 256 measurements per second.

Two circular electrodes, 8mm in diameter, were strapped onto the medial phalange of the middle and index fingers, of the non-dominant hand (Figure 2.5). The responses were measured in micro-Siemens (µs). Arousal is a broad term referring to overall activation of sympathetic responses, which reflected excitement, attention, and arousal, not limited to emotional states (Braithwaite *et al.*, 2013). EDA data were not used to compare how electrodermal patterns vary between individuals during the experience of an emotion as indicated in the self-report questionnaire. The only reason the EDA was monitored was to ensure that the emotional response was a real response and not the result of the Hawthorne Effect (Coombs & Smith, 2003).

Figure 2.5: Skin conductance sensor placement

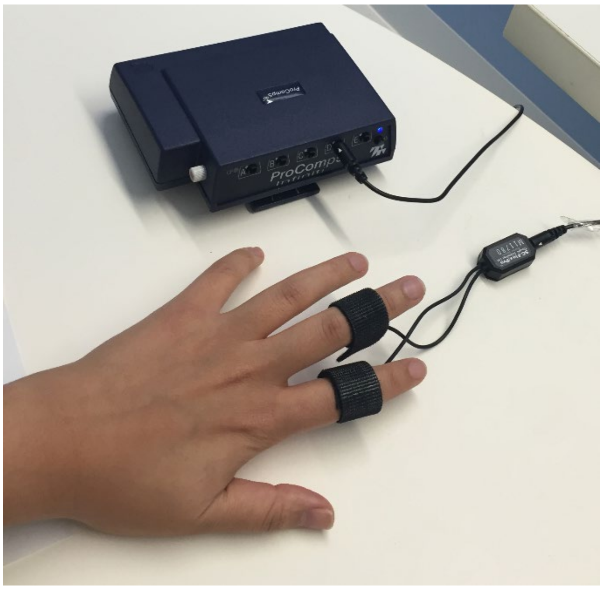


Figure 2.5 illustrates the attachment of the skin conductance sensors to the medial phalange of the middle and index fingers of the non-dominant hand of the subject.

2.6.3 Emotional Facial Behaviour

Analysis of facial behaviour involved observing facial recordings from the frontal view of the face to detect activity of facial responses from the neutral or baseline expression to the peak of an emotional facial expression for the expressions of amusement, sadness and fear.

The facial behaviour recordings were uploaded onto the computer and video footage of the frontal facial view were examined. The participants' facial behaviour was observed for a response during the scenes where the subject concurrently experienced the target emotion as stated in the self-report questionnaire and during the time at which a skin conductance response (SCR) occurred was synchronised to the frontal facial recording.

This permitted two facial image stills representative of: (1) neutral 'baseline' and (2) expressive 'peak of emotional' response for each subject to be extracted from the recorded video footage using a video editing software (Adobe Premiere Elements 13, USA). The emotional response image was extracted when the stimulated emotion was at its peak. The neutral or baseline facial expression was characterised as the neutral positioning of the facial features preceding facial movement.

The different facial image views that were extracted for each expression included:

1. The frontal
2. Profile left
3. Profile right

Of the 142 participants, image sets for the expression of amusement were captured from 96 subjects. For the emotion of sadness and fear, image sets were derived from 44 subjects. For each image set which included a baseline image along with their corresponding emotional state, a total of 6 images were extracted per emotional state. This amounted to 1104 images. The frontal facial images were subsequently coded using FACS (Ekman *et al*., 2002).

2.7 Experimental protocol (b)

Protocol b refers to the data extraction from the above protocol (Chapter 2, Section 2.5).

Feature representation is critical for facial expression analysis since it contains distinctive information on the representation of expressions. The study utilised two feature extraction methods in separate image analysis to determine the optimal feature subset to facilitate emotional facial expression recognition: (1) LK optical flow technique for global displacement of facial movements, and (2) manual annotated facial landmarks of facial images to measure displacements of a fixed set of salient points. Each extraction method required different cropping criteria to discard as much irrelevant data and/or to reduce noise.

2.7.1 Image Pre-processing

Image pre-processing was manually performed to correctly align and orient the images allowing them to be cropped to uniform pixel size using a photo editing software (Adobe Photoshop Elements 13). The process involved superimposing a grid over the top of the image. The grid divided the image into even sections both horizontally and vertically and assisted in the alignment of the face. Normalising the orientations of the face was executed according to procedures adapted from Liu *et al.* (2003) using the triangulated coordinates from three points: the inner canthus of each eye and the philtrum (Figure 2.6). The face was rotated so that the line joining each canthus (C1 and C2) was corrected to a horizontal position and as such the philtrum (C3) was located on the perpendicular line going through the midpoint of C1, C2 as guided by the grids. The face midline is defined as the line going through the midpoint of C1-C2 and C3. For profile images, the face was rotated to align with the dimensions of the frontal images.

Figure 2.6: Face normalisation

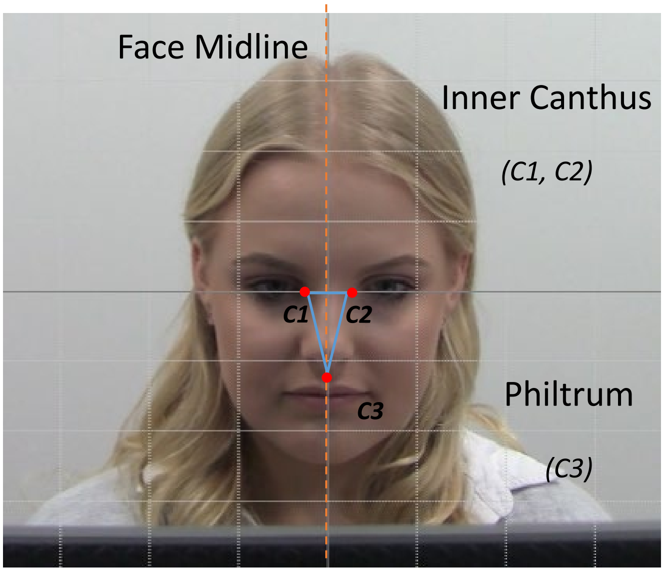


Figure 2.6 illustrates how face normalisation is achieved in an image, using the triangulated coordinates of three points: the left (C1) and right (C2) inner canthus; and the philtrum (C3) by rotating C1 and C2 into a horizontal line segment, and skewing the face such that C3 is located on the midline of C1, C2. Method adapted from Liu et al. (2003). Permission granted for use of this image.

After normalisation of the facial orientation, the image was cropped to remove extraneous non-facial data and to congruent pixel sizes pixel dimensions.

2.7.2 Lucas-Kanade Optical Flow

Images of facial expressions were cropped manually to test the performance of the LK optical flow to extract facial motion descriptors. The images were tightly cropped so as best to include the most lateral point of the soft tissue contour of the face, the hairline, and the chin with the midline vertically centred (Figure 2.7). The perimeter for the profile images extended to include the most anterior region of the face, commonly the most protruded point of the nose, the outer contours of the cheek (usually just at the hairline or in line with the jaw angle), and the chin. This was done as to minimise background noise. This was difficult in cases where expressive responses caused lengthening of facial features for certain emotion (for example amusement caused great widening of the lips) to be greater than the baseline images, this increased the area that needed to be cropped causing excessive background to appear. Images were cropped to a resolution of 380 x 380 (width x height) pixels and 250 x 380 (width x height) pixels for the frontal and profile facial images, respectively. The cropped images were saved in the lossless image format Portable Network Graphics (PNG) (Roelofs, 1999). PNG was chosen as it is a lossless compression format that reduces the size of the image without any quality loss of the image. The other form of compression is lossy (irreversible) compression where image is degraded due to information discarding (Delac *et al.*, 2008). Although data reduction is much higher with lossy compression techniques, when they are uncompressed, they tend to introduce artefacts that degrade image quality. This becomes important when trying to reduce data size to optimize computational processing during feature extraction.

Figure 2.7: Cropped expression image set

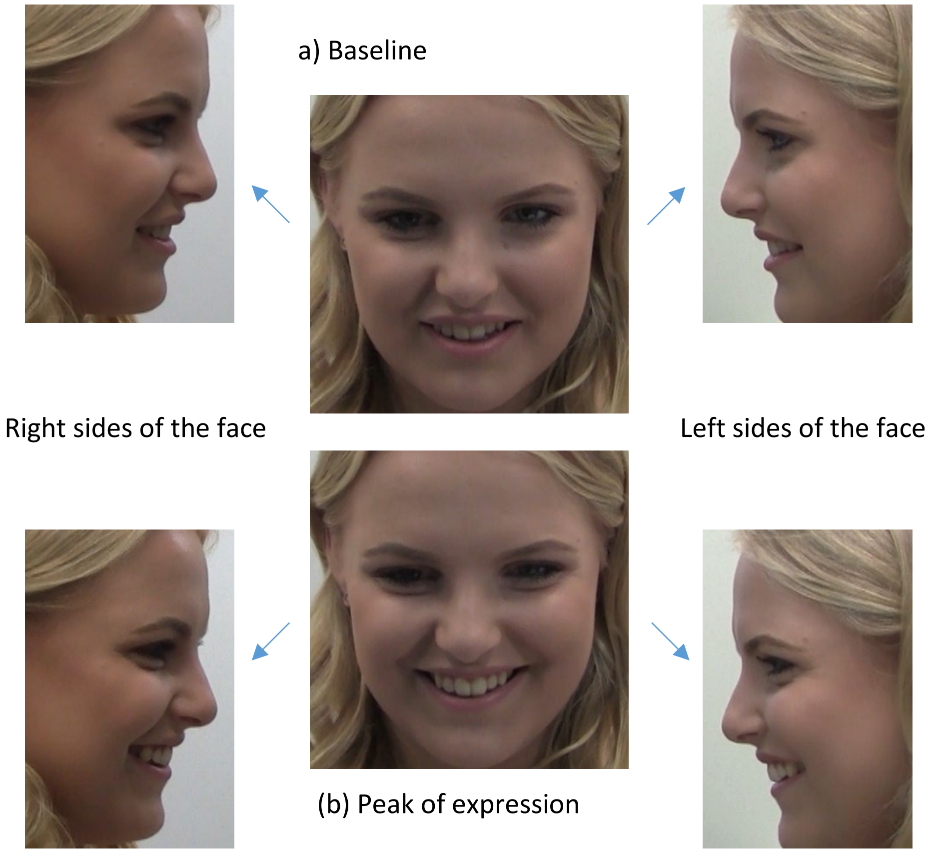


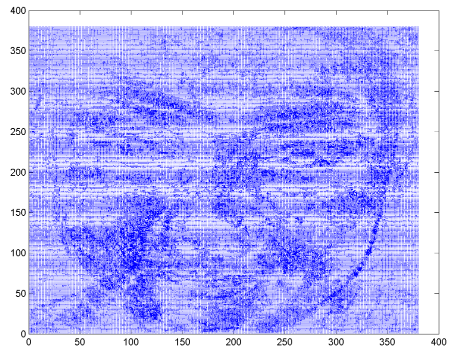
Figure 2.7 displays a cropped image set consisting of facial images representative of (a) the neutral 'baseline' and (b) 'peak' of emotional expression for amusement from the frontal and profile views. Permission granted for use of these images.

The 'MATLAB' software (Matrice LABoratory R2017b, version 9.3, USA) developed by Maths Works was used to implement an automated version of the LK optical flow algorithm (Lucas & Kanade, 1981), scripts of which for the LK optical flow were written by Dr. Budi Jap at UTS Science and had been used in previous studies within the Unit (Duthoit, 2007; Chow, 2010; Kilincer, 2011; Nguyen, 2014; Siwan, 2015; Chow *et al.,* 2019).

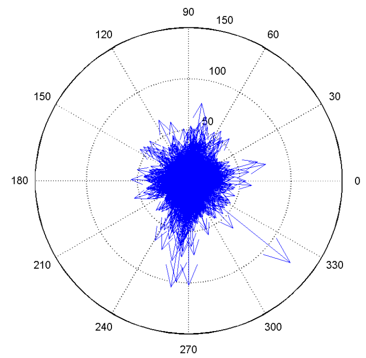
The LK optical flow algorithm compares brightness between successive frames (Patel & Upadhyay, 2013). The algorithm compares two images providing the magnitude and vector flow of facial muscles from neutral to peak of expression response by comparing the displacement of pixel intensity between images.

Results were presented in the form of a "quiver plot" and a "compass graph" (Figure 2.8). The quiver plot displays velocity as arrows with derived components (*u, v*) at the points (*x, y*). The base of each arrow is located at the origin. The direction and magnitude of the movement is represented by the location of the tip of each arrow point. These arrows present both direction and their proportionate motion within a motion field.

Figure 2.8: Quiver plot and Compass graph



(a) Quiver plot



(b) Compass graph

Figure 2.8 displays the output of the LK optical flow analysis as (a) Quiver plot which depicts vectors as arrows of motion from specific co-ordinates of origin in neutral image to amusement image. Vectors from the quiver plot were used to produce (b) Compass graph that displays the total direction and magnitude of vectors. The compass diagram is separated into 12 sectors of 30°on a 360° plane.

From the quiver plot, the algorithm produces a compass graph (see Figure 2.8b). A compass graph collates the vectors onto a circular grid made-up of twelve 30° sectors on a 360° plane based on their direction with respect to the origin. Three parameters were given: 1. The average displacement (pixels) of vectors in different sectors; 2. The total number of arrows between different sectors; and 3. The angle (degrees) of movement between different sectors.

The average vectors of movement that occurred in facial expressions between a baseline/neutral image and an emotional response was the parameter of interest for this study and used as a feature set to be fed into the classifier. The results of the analysis were used for interpretation and categorisation of facial expressions.

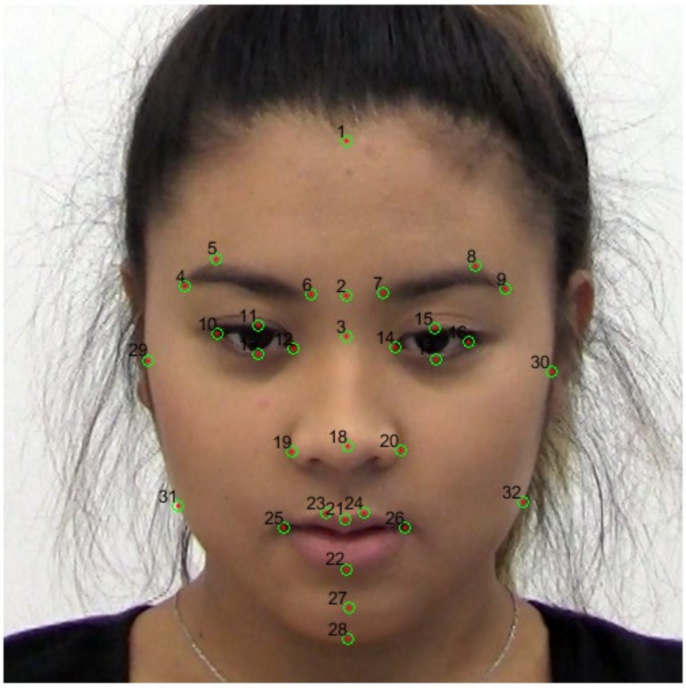
2.7.3 Facial Landmarks

Common automated image-based facial landmark detection models such as active shape models (Cootes *et al.*, 2001) are constructed based on landmarks predefined on the average face model. The landmarks are registered by aligning the human facial image with the average face model and using an iterative closest point algorithm to fine tune their predicted location. Although it is highly desirable for automation of landmark detection, the position of landmarks is not always precise. Landmarks that are poorly predicted will be positioned far from their corresponding ground truth locations leading to a wider gap in measurement error when presenting relevant data to the classifier. Therefore, in this study, facial landmarks for each image were located manually to accurately identify specific facial landmarks and subsequently increasing the quality of the dataset.

The still images were cropped to uniform pixel sizes, 450 x 550 (width x height) pixels and 250 x 550 (width x height) pixels for the frontal and profile facial images, respectively. As background noise was not an issue, this provided a larger cropping area. The images were cropped using Photoshop Elements 13 (Adobe, USA).

The study was restricted to commonly used landmarks, such as the eye corners, nose tip, nostril corner, mouth corners, end points of the eyebrows and facial contours as they were easily definable points on the individual facial images. The landmarks were selected using the soft tissue anthropometric landmarks (Farkas**,** 1994) to locate a total of 32 soft tissue landmarks for the frontal facial (Figure 2.9) and 18 landmarks for profile (Figure 2.10) images.

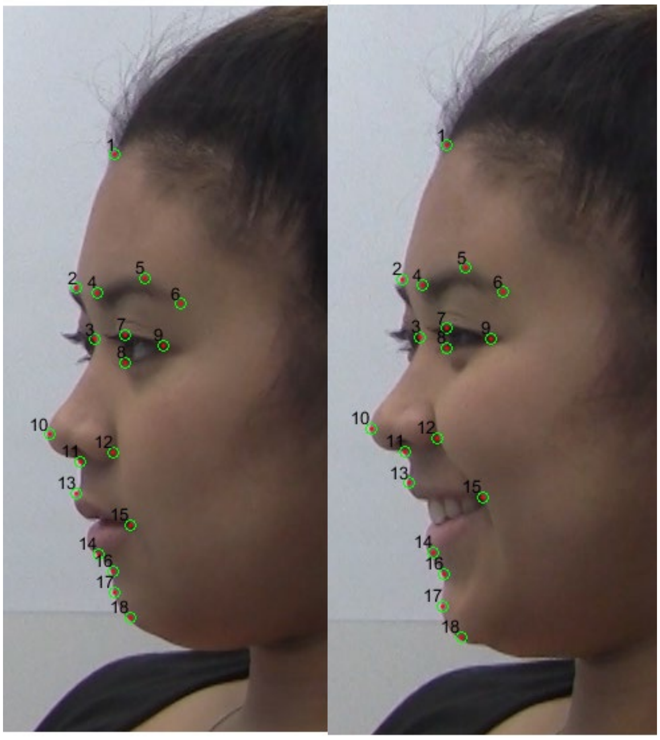
Figure 2.9: Frontal facial image and corresponding landmark table



	Frontal			**Frontal**	
1	Trichion	Tr	**17**	Left palpebrale inferius	exL
2	Glabella	g	**18**	Pronasale (Nasal tip)	prn
3	Sellion	se	**19**	Right alare	alR
4	Right lateral aspect of the eyebrow	oeR	**20**	Left alare	alL
5	Right eyebrow apex	eaR	**21**	Labiale superius	ls
6	Right medial aspect of the eyebrow	ieR	**22**	Labiale inferius	li
7	Left medial aspect of the eyebrow	oeL	**23**	Right crista philtri	cphR
8	Left eyebrow apex	eaL	**24**	Left crista philtri	cphL
9	Left lateral aspect of the eyebrow	ieL	**25**	Right chelion	chR
10	Right exocanthion	exR	**26**	Left chelion	chL
11	Right palpebrale Superius	psR	**27**	Pogonion	pg
12	Right endocanthion	enR	**28**	Gnathion	gn
13	Right palpebrale inferius	piR	**29**	Right zygion	zyR
14	Left endocanthion	enL	**30**	Left zygion	zyL
15	Left palpebrale Superius	psL	**31**	Right gonion	goR
16	Left exocanthion	piL	**32**	Left gonion	goL

Figure 2.9 illustrates the facial points extracted from frontal facial images and their corresponding landmarks. Adapted from Farkas (1994). Permission granted for use of this image.

Figure 2.10: Right profile facial image and corresponding landmark table



	Profile				
1	Trichion	Tr	**10**	Pronasale	prn
2	Glabella	g	**11**	Subnasale	sn
3	Sellion	se	**12**	Alare	al
4	Inner eyebrow corner	ie	**13**	Labiale superius	ls
5	Eyebrow apex	ea	**14**	Labiale inferius	li
6	Outer eyebrow corner	oe	**15**	Chelion	ch
7	Palpebrale superius	ps	**16**	Supramentale	sm
8	Palpebrale inferius	pi	**17**	Pogonion	pg
9	Exocanthion	ex	**18**	Gnathion	gn

Figure 2.10 is an illustration of the facial points extracted from the right profile facial images and their corresponding landmarks. Adapted from Farkas (1994). Permission granted for use of this image.

After the facial landmarks were chosen, the x and y coordinates for each of the landmark points were located on the neutral 'baseline' image. The location of the corresponding landmark in the "expressive" image was recorded (Figure 2.11a + b). The vector displacement of each facial landmark from the neutral 'baseline' to peak of emotional expression was computed by calculating the Euclidean distance between the pair of sequential points of successive images. The Euclidean distance between the two coordinates were derived by the Pythagorean theorem. The process is illustrated in

Figure 2.12. Distance (d) on a coordinate plane can be considered the hypotenuse of a right-angled triangle. Using Pythagoras theorem, the distance between the two points is the square root of the sum of the squares of the distance between the horizontal and vertical sides from each point.

Figure 2.11: Coordinates of movement of a landmark point between consecutive images

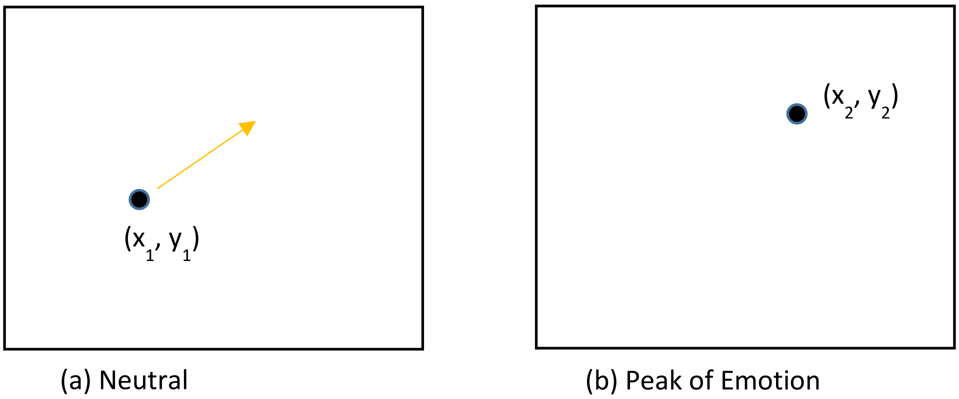


Figure 2.11 shows an example of the coordinate of a facial landmark point on (a) the neutral image and its corresponding location in the subsequent (b) "expressive" or peak of emotion image.

Figure 2.12: Computing the displacement of landmark coordinates

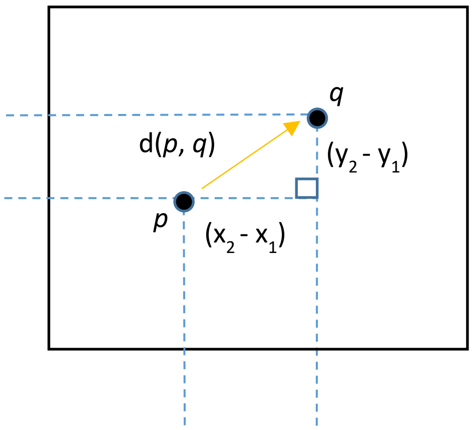


Figure 2.12 illustrates how the displacement of the landmark points between consecutive image frames were determined. Distance (d) is calculated using Pythagoras' formula:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

Using this method, feature vectors represented as the magnitude and direction of flow of each landmark were obtained. The feature vectors for all landmark points contributing to the expression of emotion were fed into the classifier for interpretation and categorisation of the facial expressions.

2.8 Classification

A classifier was implemented to assign categorical (class) labels to the images based on the feature vectors contributed from each feature extraction technique. The classifiers were trained using the Classification Learner application in MATLAB R2017 (MATrice LABoratory version 9.3, USA). The classifier used a five-fold cross validation which partitioned the data into 5 randomly chosen subsets of equal size for training and validation. This was done to ensure that there were a sufficient number sample in data in each fold that allowed for an iterative training of the classifiers. After training multiple models, summary of predicted results was given in the form of a confusion matrix which evaluated the accuracy of each classifier to discern between each emotion class.

Chapter 3 – Results: Demographics

3.1 Results

Demographics

One hundred and forty-two healthy volunteers participated in the study. All subjects were aged between 18 - 34 years, mean age = 23 years, standard deviation (*SD)* = 4.25 (males: *M* = 22.4, *SD* = 3.49; females *M* = 23.3, *SD* = 4.59). The study was made-up of a racially diverse cohort. A breakdown of racial/ethnic groups of the subject population can be viewed in Table 3.1. Where the total population consists of 52% Asian, 33% European, 4.2% Americas (1 North American, 2 Central American and 3 South American), 4.2% Middle Eastern, 0.8% African, 5.6% other or mixed heritage. Furthermore, among the 142 subjects that participated in the study 74 (52%) were born in Australia. The proportion that was born in Australia includes: 49% Asian, 36% European, 2.7% Middle Eastern, 1.4% from the Americas and 11% of other/ mixed heritage race. English was the main language spoken by 78 of the subjects (55%).

Table 3.1: Ethnic distribution of study population

			Place of birth		
Background	Number	Percentage	AUS	Overseas	English main Language
Asia	74	52.1	36	38	31
Europe	47	33.1	27	20	35
Middle East	6	4.2	2	4	1
Americas	6	4.2	1	5	3
Africa	1	0.7	0	1	1
Other/ mixed heritage	8	5.6	8	0	8
Total	142	100	74	68	78

Table 3.1 shows the breakdown of the research cohort based on their ethnic origin, Australian born and English main language spoken.

Key: AUS = Australia

3.2 Discussion

Past studies have attempted to recruit subjects from three different age categories: 18-34, 35-49, and 50-65 years. There have been challenges in recruiting eligible subjects from the age brackets 35-49 years and 55-65 years that met the eligibility criteria (Chow, 2010; Kilincer, 2011; Siwan, 2015; Chow *et al.*, 2019). According to Nyugen (2014) the use of medication was common in the older demographic group due to the prevalence of chronic diseases/illness such as diabetes and mood disorders which prevented participation. As a result, the stronger presence of younger volunteers.

Another consideration was the population distribution within the local Sydney region. According to the City of Sydney council (2020) almost 50% of the local residents were aged between 18-34 years with the largest group being 25-29 years making up 18.1% of the resident population. This is closely followed by the age groups: 30-34 years, and 20-24 years which accounts for 14.8% and 13.9% of the total persons respectively (ID – the Population Experts, 2019). Given the population distribution of the Sydney city area, and previous difficulties in recruiting participants for all three demographic age ranges, the study was restricted to adults 18-34 years.

Seeing that the Australian population is one of the most ethnically diverse in the world (Australian Government, 2016), it was expected that it would result in an ethnically diverse study population. This was reflected in the recruitment of volunteers who were from a culturally diverse background.

Chapter 4 – Results: Self-report questionnaire

4.1 Results

Self-Reports

The self-report responses to the short film clips were used to evaluate the effectiveness of the emotion film stimuli to elicit emotions. The mean intensity ratings were computed for each of the sixteen emotion items. Statistical analyses was conducted to evaluate the effects of gender on emotion intensity in response to watching the emotion stimuli, using independent sample t-tests. The t-test compares the differences in means between two independent groups, as such the mean intensity rating across all emotions was compared between males and females for each film (Glynn & Weisbach, 2009). Independent sample t-tests was also used to assess what effect ethnicity had on rating of the self-report by comparing the mean intensity levels of emotion between the two largest cohorts, that is, between people of European (which included, Northern, Southern, Eastern, and Western parts of Europe) and Asian (which included, Northern, Southeast and Southern Asia) ancestral background. The results of a t-test are implied through t-values (t) and the degrees of freedom (df) to determine the statistical significance. The level of significance is set to 0.05.

To evaluate how effective the films were in producing discrete target emotions, the difference in mean intensity ratings for all sixteen emotions were compared within each film. When comparing three or more group means where the participants are the same for each group, a within-subject or repeated measures analysis of variance (rmANOVA) is often applied (Laerd Statistics, 2018). This includes situations where participants are surveyed multiple times or subjected to multiple conditions. For each of the short films, a 16-level within-subjects ANOVA was conducted followed by Bonferroni post hoc analysis for pairwise comparisons between the target emotion and each non-target emotion.

Gender and Ethnicity

To provide an estimate of the effects of gender, independent sample t-tests were performed to compare mean intensity rating of all emotions between males and females as given by the self-report. Independent sample t-tests revealed there were no differences between gender for each of the emotion types with the exception of tension during the viewing of "N*ever say no to Panda*" film stimulus. Males reported greater level of tension than females ($t(59) = 2.049$, $p < 0.045$).

The mean levels of intensity of emotions reported by gender are recorded in Table 4.1. It was generally observed that males reported higher levels of positive emotions, exhibiting happiness, contentment and relief, whilst females reported experiencing general higher levels of arousal across all films. There was no gender difference in ratings of amusement, during the viewing of the film stimuli "*Never say no to Panda*" ($t(140) = -1.171$, $p < 0.244$), sadness ($t(140) = -0.181$, $p < 0.857$) and fear ($t(140) = -0.686$, $p < 0.494$) during the viewing of "*Last Minutes with Oden*" and "Lights Out" short films respectively. For the amusement film stimulus, women rated amusement higher than men with a mean valence rating of 4.61 compared to males at 4.17. They also reported higher levels of sadness (women = 4.67, men = 4.50) and fear (women = 4.48, men = 4.20) than men with their respective stimulus.

Table 4.1: Mean intensity levels (Standard deviation) of emotion by gender

Film stimulus (Target emotion)	Panda Cheese commercial (Amusement)		Last Minutes with Oden (Sadness)		Light's Out (Fear)	
	Male	Female	Male	Female	Male	Female
Amusement	4.17 (2.42)	4.61 (2.04)	0.13 (0.38)	0.09 (0.30)	1.58 (2.21)	1.19 (1.83)
Anger	0.17 (0.44)	0.29 (0.81)	0.28 (0.75)	0.25 (0.91)	0.21 (0.58)	0.21 (0.76)
Arousal	0.07 (0.24)	0.27 (0.92)	0.06 (0.31)	0.23 (0.98)	0.17 (0.91)	0.44 (1.30)
Confusion	1.02 (1.33)	0.87 (1.18)	0.97 (1.01)	1.22 (1.19)	0.86 (1.49)	0.99 (1.45)
Contempt	0.22 (0.67)	0.31 (1.10)	0.18 (0.55)	0.11 (0.38)	0.44 (1.07)	0.15 (0.57)
Contentment	0.63 (1.30)	0.61 (1.37)	0.18 (0.46)	0.22 (0.78)	0.17 (0.57)	0.09 (0.39)
Disgust	0.19 (0.49)	0.20 (0.55)	0.09 (0.40)	0.07 (0.27)	0.36 (0.86)	0.39 (0.86)
Embarrassment	0.23 (0.61)	0.16 (0.59)	0.13 (0.39)	0.04 (0.16)	0.48 (1.09)	0.43 (1.22)
Fear	0.15 (0.52)	0.10 (0.33)	0.59 (1.13)	0.92 (1.42)	4.20 (2.18)	4.48 (2.41)
Happiness	2.68 (2.35)	2.67 (2.40)	0.31 (0.67)	0.25 (0.63)	0.39 (1.32)	0.20 (0.82)
Interest	1.99 (2.20)	2.17 (2.16)	1.56 (1.90)	1.58 (2.16)	1.81 (1.88)	1.71 (1.83)
Pain	0.04 (0.16)	0.05 (0.29)	1.60 (1.90)	2.10 (2.37)	0.34 (0.95)	0.30 (1.05)
Relief	0.40 (0.83)	0.36 (0.93)	0.49 (0.97)	0.47 (0.92)	0.45 (1.17)	0.54 (1.09)
Sadness	0.11 (0.39)	0.04 (0.20)	4.50 (1.86)	4.67 (1.92)	0.12 (0.49)	0.17 (0.67)
Surprise	1.56 (1.52)	1.72 (1.66)	0.46 (0.93)	0.50 (1.12)	2.85 (2.02)	2.91 (2.07)
Tension	0.63 (1.38)	0.21 (0.61)	1.44 (2.02)	1.56 (2.06)	3.91 (2.51)	4.09 (2.44)

Table 4.1 displays the mean intensity levels and standard deviation (SD) of emotion by gender. Summary of the mean intensity ratings and standard deviation for 16 emotional terms for each emotion eliciting shorts for male and female participants.

Note: Mean intensity values marked in red indicates a significance difference in mean intensity rating between gender at the p < 0.05 significance level as determined by the repeated measures analysis of variance (rmAVONA).
Key: SD = Standard Deviation

When assessing the effects of ethnicity between subjects, independent sample t-tests were performed to compare the mean intensity level between people of European and Asian ancestral background as they represented two largest cohort in the study. When looking at the subjects' rating of emotions according to ethnicity, Asian people reported greater levels of intensity across the board for all three films except for arousal. They also reported lower level of feelings of amusement and embarrassment for the fear stimulus, and amusement, fear, and pain for amusement stimulus. However not to a level of statistical significance ($p < 0.05$). For the amusement film stimulus, the effect of ethnicity as a subject variable on self-report ratings of emotion was non-significant $t(119) = -0.066$, $p < 0.948$. Similarly, analysis revealed no significant effects for sadness $t(113)$ = -

0.100, $p < 0.921$ and fear $t(119) = -0.751$, $p < 0.454$ with their respective film stimuli. The analysis suggested no difference in the mean level ratings of emotional intensity between people of European and Asian ancestral background.

Furthermore, analyses of the self-report questionnaires also revealed no difference in ratings between fluent English speakers compared to non-fluent English speakers for all three short film clips that aimed to elicit amusement ($t(118) = 1.684$, $p < 0.95$.), sadness ($t(140) = -0.45$, $p < 0.964$.) and fear ($t(140) = -0.637$, $p < 0.525$).

There was no difference in the ratings between people whose dominant language spoken was English compared to those of non-English speaking background. However, it was generally observed that English speakers reported lower levels of intensity except for amusement, anger, fear and tension for the "*Never say no to Panda*" commercials, interest for "*Last minutes with Oden*" film, anger, arousal, and contempt for the "*Lights out*" short film.

Discreteness of target emotions

Upon evaluating the self-report, it was important to assess whether the films induced the intended target emotions, in particular, testing the distinctiveness of each clip in eliciting the target emotion. To determine whether each film clip elicited expected 'discrete' emotional states indicated through self-reports, the study operationalised 2 key aspects of the self-reports: intensity and discreteness.

The intensity represents the strength and magnitude of emotion felt by the volunteers, determined by calculating the mean level intensity rating for each emotion for each film. Discreteness indicates the success index of the emotion eliciting film clip to elicit a particular emotion. It was operationalised by deriving an idiographic hit rate index that reflected the percentage of participants who indicated they felt the target emotion at least one point more intensely than the other non-target basic emotions for a given clip (Gross & Levenson, 1995).

Mean ratings across the sixteen emotion terms for all film clips were generated and are presented in Table 4.2. Examination of mean intensity ratings of emotions for each short film showed that amusement was the highest reported emotion felt during viewing of the “*Never say no to Panda*” commercials. Likewise, sadness and fear yielded highest mean intensity rating for “*Last minutes with Oden*” and “*Lights Out*”, respectively.

Table 4.2: Intensity mean values (SD) for emotion self-reports

Film stimulus	Panda Cheese commercial	Last Minutes with Oden	Light's Out
Target emotion	*Amusement*	*Sadness*	*Fear*
Amusement	4.26 (2.18)	0.11 (0.33)	1.33 (1.96)
Anger	0.25 (0.70)	0.26 (0.85)	0.21 (0.70)
Arousal	0.20 (0.76)	0.17 (0.81)	0.35 (1.17)
Confusion	0.92 (1.23)	1.13 (1.13)	0.94 (1.45)
Contempt	0.28 (0.97)	0.14 (0.45)	0.25 (0.79)
Contentment	0.62 (1.34)	0.20 (0.68)	0.12 (0.46)
Disgust	0.20 (0.53)	0.08 (0.32)	0.39 (0.90)
Embarrassment	0.18 (0.59)	0.08 (0.26)	0.45 (1.17)
Fear	0.12 (0.40)	0.80 (1.33)	4.39 (2.32)
Happiness	2.67 (2.37)	0.27 (0.64)	0.27 (0.94)
Interest	2.11 (2.16)	1.57 (2.06)	1.75 (1.83)
Pain	0.04 (0.25)	1.92 (2.22)	0.31 (1.01)
Relief	0.37 (0.89)	0.47 (0.93)	0.51 (1.10)
Sadness	0.06 (0.28)	4.54 (2.00)	0.15 (0.60)
Surprise	1.66 (1.6)	0.48 (1.05)	2.89 (2.04)
Tension	0.36 (0.97)	1.52 (2.03)	4.02 (2.44)

Table 4.2 displays the mean intensity and standard deviation for each film clip’s target emotion.

Note: Mean intensity values marked in red indicate a significant difference in mean intensity rating compared to all other emotion categories at the p < 0.05 significance level as determined by the repeated measures analysis of variance (rmAVONA).
Key: SD = Standard Deviation

When comparing the discreteness level (Table 4.3) to non-target basic emotions “*Never say no to Panda*” clip elicited amusement effectively, attaining a mean level of 4.26 (*SD* = 2.18), and discreteness of 79.58%. Likewise, sadness yielded a mean level of 4.54 (*SD* = 2.33), and discreteness 83.80% for the film “*Last minutes with Oden*” indicating good reliabilities across the participants. The short film “*Lights Out*” elicited high levels of fear, with an intensity mean level of 4.34 (*SD* = 2.00), but a discreteness of 50.70%. Meaning that although subjects reported high levels of fear, the experience of fear was not felt discretely by many.

Table 4.3: Mean intensity (SD) rating and discreteness score (percentages) for the highest elicited emotion for each film stimulus

Emotional Film	Emotion	Mean Rating (0-8 scale) (*SD*)	Discreteness (hit rate %)
Never Say no to Panda	Amusement	4.26 (*2.18*)	79.58%
Last Minutes with Oden	Sadness	4.54 (2.00)	83.80%
Light's Out	Fear	4.39 (*2.32*)	50.70%

Table 4.3 displays the mean intensity for the highest rated emotion for each short film clip as well as the corresponding discreteness (hit rate). Discreteness is measured as the percentage of participants rating each target emotion at least one point above all non-target basic emotions.

Key: SD = Standard Deviation

To assess whether the mean rating for the target emotions: amusement, sadness and fear was rated highest at a significant level above the other 15 non-targeted states, a within-subject comparison of emotion rating for each film was conducted. More specifically, 16-level within-subjects ANOVA comparing the mean intensities of all rated emotions for each clip, with Bonferroni correction for multiple comparisons. This is used when comparing more than 2 groups to reduce the chances of incorrectly rejecting the null hypothesis or type 1 errors. In cases for which assumptions of sphericity had been violated, estimates were made using Greenhouse-Geisser method where epsilon (ε) was <0.75, Huydt-feldt technique where epsilon (ε) was >0.75, (Howard, 2014; Uhrig *et al.*, 2016).

Analysis revealed a significant difference in emotion rating for the viewing of the amusement and sadness stimuli with "*Never say no to Panda*" $F(4.88, 688.67) = 152.39$, $p < 0.001$, $\varepsilon = 0.326$ and "*Last Minutes with Oden*" $F(5.97, 841.49) = 143.65$, $p < 0.001$, $\varepsilon = 0.398$ eliciting amusement ($p < 0.001$) and sadness ($p < 0.001$) at a higher level of significance above any other emotion respectively. A follow-up comparison indicated a significant difference in emotion rating between amusement and 15 non-target emotion ($p < 0.001$). Similarly, sadness, as rated significantly higher than all of the other 15 nontarget emotions, meaning subjects reported significantly greater sadness and amusement than any other emotion for their respective film stimulus.

Significant main effects for between emotion ratings were observed for the fear stimulus, "*Lights Out*", ε = 0.400; F(6.00, 846.18) = 153.99. Fear was reported significantly higher than all other non-target emotions except for tension which was rated at similar levels to fear (fear= 4.39, tension =4.02) and was not statistically different (t_{141} = 1.901, p = 0.059).

Order Effects

Order effects refer to differences in research participants' responses that result from the order (e.g., first, second, third) in which the experimental materials are presented to them (Cleophas, 1999). One particular order effect is carryover effect. A carryover effect occurs when the effects of an experimental condition or treatment carries over to the next (Cleophas, 1999). These effects are more likely when the experimental conditions follow each other quickly. In this instance, depending on the order at which the emotion stimulus was played, any lingering effects from viewing the previous short film clip may influence perception of subsequent clips.

As the emotion stimuli were presented in a randomised order, data was sorted to test whether the target emotion rating was affected by the order in which the film were played. This may reveal as to whether the responses have been impacted from the previous emotion stimulus being played. Each target emotion rating of amusement, sadness, and fear for their respective film stimulus were grouped based on whether they were played first, second or third. A one-way analysis of variance (ANOVA) was conducted to evaluate the null hypothesis that there were no differences in rating of amusement when viewing the amusement stimulus based on the sequence at which the stimulus was played. The independent variable, sequence included 3 groups, representing the order of which the clip was played first (M = 4.667, SD = 1.964, n = 48), second (M = 4.190, SD = 2.450, n = 50) or third (M = 4.528, SD = 2.113, n = 44). Partial eta-squared (η_p^2) was used as the effect size for F-tests and represents the percentage of variance accounted for in the dependent variable (intensity rating) by the independent variable (ethnicity). Effect sizes are interpreted following Cohen's guidelines (1977): a partial η^2 of 0.01 ,0.06, and 0.14 are considered as small, medium and large, respectively.

Analysis revealed no statistically significant difference between groups as determined by one-way ANOVA for amusement $F(2,139) = 0.614$, $p = 0.543$, $\eta_p^2 = .009$. No significance for sadness during the sadness stimulus $F(2,139) = 2.705$, $p = 0.070$, $\eta_p^2 = .037$ regardless of whether it was played first ($M = 4.102$, $SD = 2.128$, n = 47), second ($M = 4.553$, $SD = 1.750$, n = 45) and third ($M = 4.570$, $SD = 1.975$, n = 50). Likewise, ANOVA was not significant for fear $F(2,139) = 0.165$, $p = 0.848$, $\eta_p^2 = .002$ regardless of whether it was played first ($M = 4.394$, $SD = 2.749$, n = 47), second ($M = 4.521$, $SD = 2.295$, n = 47) and third ($M = 4.246$, $SD = 1.912$, n = 48). Suggesting no order effects, as there were no significant differences in the intensity rating of emotion regardless of the order the films were played. This study confirmed that the randomised presentation of the film stimuli did not influence the participants responses that resulted from the order in which the film stimuli were presented to them.

4.2 Discussion

Emotion induction

Despite the many methodological and ethical challenges of eliciting emotions under controlled and replicable conditions, several protocols have found success in inducing emotional states in laboratory settings (Gross & Levenson, 1995; Rottenberg *et al.*, 2007; Cabral *et al.*, 2017). Films has been shown to reliably elicit emotions with relatively low demand characteristics in an experimental setting that abide by ethical guidelines (Rottenberg *et al.*, 2007; Uhrig *et al.*, 2016).

Due to strong association with ASB (Deater-Deckard *et al.*, 2007; Sharma *et al.*, 2015), the analysis of the facial expression of anger would have been an appropriate and desired emotion to study, however it is considered one of the most difficult emotions to elicit under experimental conditions (Gross & Levenson, 1995; Harmon-Jones *et al.*, 2007). Whereas other emotions can be induced using films, attempts to induce anger with films have been met with little success (Philippot, 1993; Gross & Levenson, 1995). Researchers often require the use of manipulations involving deception or interpersonal interactions (Gottman & Levenson, 1992; Cabral *et al.*, 2017; Poole & Gable, 2018). A study by Cabral and colleagues (2017) attempted to induce anger through planned conflictual social interaction, exchange of text messages, and video call. However, their study focused on the measurement of muscle activity with electromyography (EMG) such as the *corrugator supercilii* muscle, yielding moderate levels of activity associated of anger in participants.

Furthermore, evoking anger to the level of behavioural expression in the laboratory may be problematic from an ethical point of view. The reasons being, anger is elicited in response to a wrongdoing that motivates individual to resolve the tension through active behaviours (Williams, 2017; Poole & Gable, 2018). Thus, in case of any actions that stem from anger provocation placing participants and researchers under any real and immediate danger was not an option. Due to the unsafe and difficult nature of evoking anger through 1142, the facial expression of anger was not instigated in the current investigation. In this exploratory study where successful elicitation of emotions was prudent to allow for identification of natural basic emotions in subjects, it was decided to limit the study to emotions that were believed to be simplest to induce under laboratory conditions, and these were amusement, sadness, and fear.

Self-reports

As this research intended to reflect the true nature of facial expressions, facial images chosen for the study were those demonstrating coherence between facial responses and emotions reported by the subjects. It was expected that participants would report emotion-specific subjective experience, namely greater amusement in response to the clip selected to elicit amusement, greater sadness, and fear in response to the clip selected to elicit sadness and fear, respectively.

The self-report questionnaire used was adapted from of Gross and Levenson's (1995) nine-point Likert scale. In this 9-point scale, participants were asked to assess, if felt the intensity of reported emotions from a list of 16 emotions, from ''nothing'' (0) to ''extremely'' (8). The self-report format was chosen as it offered a wider measure of differentiating discrete emotional states. There were concerns that by broadening the range of emotion terms the subjects may be led to having felt multiple emotions concurrently resulting in greater degree of blending. This was seen in the results as it was found that subjects often registered having felt more than one emotion, reflected in the variability in the discreteness and intensity of the emotional responses across target emotion categories.

Gender and Ethnicity

When comparing gender-related differences in the experience of emotions, males and females did not differ significantly in their experience of specific emotions during the viewing of either the amusement, sadness or the fearful film stimulus which is similar to those reported in several previous studies (Kring & Gordon, 1998). A study by Kring and Gordon (1998) whereby participants were presented with films designed to elicit the emotions of happiness, sadness, fear and disgust, reported that both men and women did not differ in their reports of experienced emotions. Although in other works, Deng *et al*. (2016) observed gender differences in emotional responses with women experiencing greater emotional intensity, particularly for negative emotions and men had stronger emotional experiences with anger inducing and positive stimuli. This pattern was partially observed in this study as males reported reported higher levels of positive emotions, in particular, during the viewing of the negative stimuli, exhibiting happiness, contentment and relief, whilst females reported experiencing general higher levels of arousal across all films, however, these differences were marginal and not at a level of significance.

No difference was found in intensity ratings between people of English-speaking background compared to those of non-English speaking background which indicates that language was not a barrier. Likewise, no cultural differences were found in this study when comparing the mean intensity level between people of European and Asian ancestral background. Indicating that similar emotions are experienced in similar situations between Asian and European cultures.

Amusement

During the viewing of the amusement stimulus, most subjects reported experiencing feelings of amusement with a discrete hit rate of 79.58%. Amusement is a positive emotion that is associated with laughter and from a motivational perspective, shared amusement enhances pleasant interactions, creating a social bond among social groups (Fredrickson, 2003; Likowski *et al*., 2011). As such, happiness was often reported by most participants and experienced in conjunction with amusement, almost having a complimentary effect.

On the contrary, some individuals reported initial confusion which suggests ambiguity of the context at the beginning of the film which also evoked some responses of surprise. Confusion is a state of uncertainty that results from processing information that evokes more than one idea (Ellsworth & Scherer, 2003). Therefore, in this study, the unintended elicitation of confusion led some participants requiring more time to interpret the stimulus and the relevance of the Panda mascot. This was evident as the clip progresses, the realisation of the Panda's silent and violent outburst at people for not wanting to try the cheese becomes apparent, then there is a decrease in the intensity of confusion reported and an increase in amusement felt. Furthermore, the feeling of contentment and relief once they were able to understand what was occurring.

Among one of most important distinctions in the elicitation of emotions involves "appraisal" which entails the subjective evaluation of events and situations, which allows the individuals to assign different meanings to various events (Frijda, 1986; Lazarus, 1991). Those meanings, judgments, and appraisals one attributes to situations accounts for the variability of emotions experienced. For example, in the event of being mistreated, one person may feel angry, while another person may feel guilty depending on their appraisals of the cause of mistreatment. This was seen during the amusement film stimulus where a few subjects reported feelings of anger and/ or contempt interpreting the Panda's tirade as a wrongdoing or sympathising with Panda taking offence to the cheese being rejected which can generate feelings of anger (Leary *et al*., 2006).

Nonetheless, interest was experienced during all three viewings of emotional stimuli (refer to Table 4.1). Interest is related to appraisals of novel-complexity and coping potential, having evaluated an event as new, unexpected, or unfamiliar yet possessing the ability to comprehend the situation (Silvia, 2005). As such, the stimulus generates curiosity and fascination thus capturing attention. This may be responsible for sustaining a level of engagement and attention towards the stimulus.

Sadness

It has also been acknowledged that films are a direct object of appraisal capable of stimulating emotions through empathy (Visch & Tan, 2009). Empathy refers to the ability of an individual to perceive and understand the emotional state of others (Chakrabarti & Baron-Cohen, 2006) and experience resultant, related emotions (Myers *et al.*, 2009). Moreover, films evoke sadness upon observation of suffering and/or torment being viewed, relying on empathy to generate the experience of a similar emotion. Individuals develop empathy though life experience, so to have had the same or similar encounter/event in their own lives, may relive/re-feel what the person on screen is and thus anticipate what they are feeling. This in turn triggers this emotion (along with corresponding physical and neurological responses) (Eklund & Meranius, 2020).

Feelings of sadness, stem from grief associated with irrevocable loss or helplessness about such a loss (Smith & Lazarus, 1993; Shirai & Suzuki, 2017). This loss may occur in a wide range of domains, including relationships (e.g., loved one), material possessions (e.g., house), and economic circumstances (e.g., employment). The theme of loss was highlighted in the sadness stimulus showing the grief endured by the main character at the loss of his beloved dog. Among sadness, pain and tension were also experienced where the intensity levels of sadness and pain were greater in people who teared up during the film. This was also observed in a study by Gross and colleagues (1994) who elicited sadness using excerpts from the film Steel Magnolias. They showed that pain was generally associated with sadness, particularly in those who cried, also exhibiting greater expressive behaviour. As for the presence of tension, it was thought to occur in anticipation of a resolution to an internal conflict surrounding ending a life.

Moreover, relief was also experienced in some individuals which was unexpected, however, in hindsight, it would seem likely given that relief occurs either when an ongoing unpleasant emotional experience ceases or upon learning that it will end sooner than was expected (Sauter, 2017). Given the context, it shares a similar sentiment as the doctrine of double effect which asserts that, an action in the pursuit of a good outcome is acceptable, even if it achieved through means with an unintended but foreseeable negative outcome (Olsen *et al*., 2010). Therefore, evocation of relief in understanding that the pain and suffering endured by Oden the dog would come to an end, and the acceptance of death as ending the pain. Which may also explain why where some level of contentment was felt where relief was experienced.

Given that the sadness-inducing film dealt with the theme of loss, it was hoped that people could project their situations to empathise with the storyline. However, there were a select few that did not report any feelings. One possible explanation was that they did not identify with the situation, whether they did not own a pet, or have yet to experience the extent of grief and loss to empathise with the character.

Fear

The fearful stimulus plays on the theme of fear of the dark, which is a common phobia in many children and, in some adults, (King *et al*., 2005). Whilst omitting any dialogue, the film relied on the heavy use of visual imagery and auditory tropes such as the “jump scare” where there is a prolonged period of silence, followed by loud sound to enhance emotional impact (Martin, 2019).

During the viewing of the fearful film, subjects reported feelings of fear at high intensity levels but also elicited a greater range of emotions of both positive and negative valence. This may have accounted for the low discreteness rate despite fear attaining the highest intensity value.

Furthermore, surprise and tension demonstrated a strong relationship with fear. Fear and surprise have been known to be often associated with each other with the co-existence of the two emotions labelled as ‘fearfully surprised’ (Du & Martinez, 2015). The feeling of tension is generally associated with fear, alongside the build-up of suspense which can arise from events associated with conflict, dissonance, and instability (Lehne & Koelsch, 2015). As such the release of tension upon the revelation of the threat, and in similar manner to sadness, the negative affect converts to sigh of relief upon the ending of the film.

On the other hand, there were some individuals who enjoyed viewing the horror film, this was seen as reported enjoyment and amusement felt by a number of participants. In many cases amusement was accompanied by fear. Although the individuals may be attributing those feelings to that of thrill or sensation seeking which semantically, bears a resemblance to the mixture of the two emotions (Buckley, 2016). The general personality trait of sensation seeking has been implicated in the horror preference and/or enjoyment of horror. Sensation seekers tend to seek out varied, complex and novel experiences that deliver intense sensations (Zuckerman, 2001). An intense negative stimulus that maximises arousal, such as a horror film might be interpreted by a person intent on sensation seeking as being pleasant and therefore would experience a positive emotion. Conversely, a person not sensation-seeking would find the stimulus highly unpleasant.

Furthermore, watching movies carries limited risk. Effecting negative emotions experienced through watching a fearful film is in sharp contrast to negative emotions experienced in dangerous real-life situations. Thus, the volunteers whilst watching the fearful film were safe in the knowledge that no real physical harm will be caused by viewing the stimulus. Though there are exceptions for those who found the fear stimulus highly distressing and on two occasions the film had to be stopped for a period of time.

Overall, results indicated that amusement was the greatest reported emotion felt during viewing of the amusement stimulus. Likewise, sadness and fear yielded greatest mean intensity rating for sad and fearful stimuli, respectively. In addition, the idiographic hit rate percentages for verifying the success of the films in producing the targeted emotional reactions in individuals revealed that amusement and sad film stimuli were successful in eliciting discrete emotions of amusement and sadness in 79.58% and 83.8% of participants compared to the fear stimulus which elicited discrete fear in only 50% of participants. The results support the findings of previous studies (Gross & Levenson, 1995; Schaefer *et al*., 2010; Cabral *et al*., 2017) that the use of film as an effective method for eliciting emotional experiences, but only for some emotions. As such careful consideration should be taken in choice of films as the success of short films in eliciting specific emotions is very much perceiver dependent.

Chapter 5 – Results: Electrodermal responses

5.1 Results

To assess whether facial expressions were associated with physiological arousal, the change in skin conductance were recorded. The skin conductance response (SCR) is an independent index of sympathetic activity that is frequently used as an indirect measure of attention, arousal, and cognitive effort (Zhang *et al*., 2017). As previous research has established that skin conductance will vary systematically in conjunction with emotional arousal (Khalfa *et al*., 2002; Gatti *et al*., 2018), it was expected that changes in skin conductance in EDA readings in subjects would act as a physiological indicator of emotional arousal during emotional expression responses.

Since SCRs are generated by sweat secretion initiated by distinct bursts of sudomotor nerve activity (Boucsein, 2012) from subsequent autonomic arousal, EDA readings have been shown to have up to 5 second latency (stimulus to onset time) of activation of emotional facial expression. Furthermore, the onset of the SCR is typically between 1 and 5 seconds after the delivery of the stimulus (Boucsein, 2012). As such, it would be expected that the SCR would not exactly coincide with the initiation of facial activity, this was what was seen when syncing EDA with video recordings. Therefore, conductance responses that occurred within a 5 second window period of a facial activity response were taken as the event-related SCR.

The SCR was determined by manually identifying the peak SCR (µS) from the recording in which the film stimulus selected to elicit either amusement, sadness or fear was viewed and deriving the difference between the baseline/ or onset and peak response values (Figure 5.1). The measurement was for the duration of the onset to peak SCR. The images of the evoked emotional response were extracted during this peak period.

Figure 5.1: Electrodermal Activity reading for subject viewing of an emotion stimulus

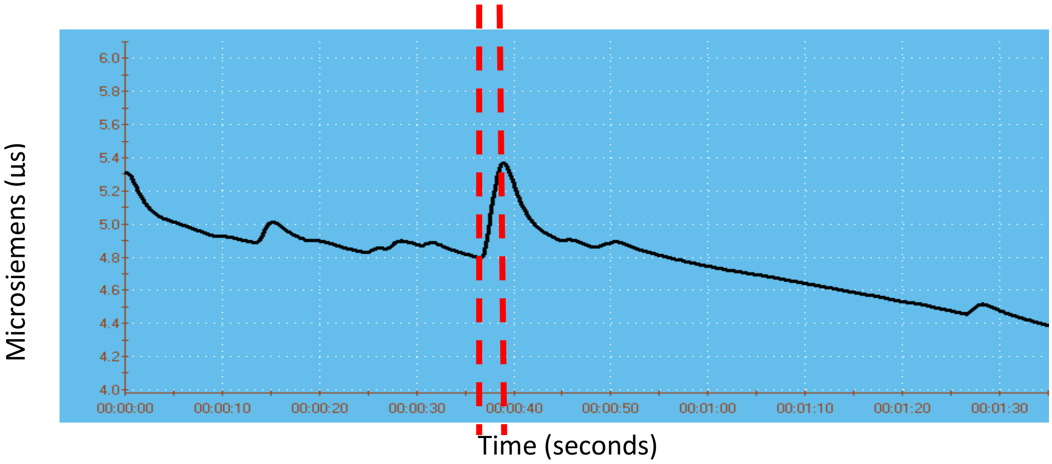


Figure 5.1 displays an example of an electrodermal activity reading and skin conductance response corresponding to the facial activity for a subject who reported experiencing amusement during the viewing of the "Never Say no to Panda" clip.

Key: µs = Microsiemens

Extracting EDA for subjects who reported feelings of sadness proved difficult as it was seen that for the majority of individuals responding to a sad stimulus, subjects who affirmed that they had felt the emotion sadness, exhibited a flat or decreasing EDA response without peaks. This pattern of response suggests a reduction in sympathetic activity (Khalfa *et al*., 2002; Marsh *et al*., 2008). However, SCR was observed in others who reported feelings of sadness and signs of crying, i.e., marked by visible tears, changes in skin colour, vocal sobbing, which may have stimulated sympathetic response. Thus, EDA could not be extracted and was not used as an indicator for sadness expression in this study. If the volunteers identified themselves to have experienced sadness during the viewing of the sadness film through the questionnaires, and no peaks were shown in the EDA, and facial activity was observed in the video recordings, responses were considered to have occurred. Hence for those volunteers, the image of the evoked emotional response was taken from the aligned self-reports, facial activity, and EDA when possible. However, if not, the self-reports and facial activity were used in the case for sadness.

The SCR representing neutral facial image was taken as the onset of the SCR and emotional response correlated with the peak SCR. SCR time varied between expressions, with the response functions mainly differing in peak latency. The general trend observed across readings showed presence of SCRs for the emotion of amusement, and fear whilst the viewing of the sadness stimulus was associated with reduced skin conductance level.

The mean amplitude of skin conductance response during facial activity for amusement was 0.310µS, SD = 0.32µS with an average rise time from onset to peak conductance of 3.6 seconds. This was taken across 96 subjects. In contrast the mean skin conductance response for fear was 0.61µS, SD = 0.54µS across 44 subjects and an average rise time of 4.4 seconds. SCR arising in conjunction with the facial activity of the amusement and fearful state substantiated the occurrence of an emotional response. With regards to the experience of sadness, facial activity was seen 44 subjects, at which only 28/44 (52%) showed skin conductance activity in conjunction to facial activity movements, 13 displaying visible signs of crying. Whilst the other 21 subjects showed a decrease in baseline tonic EDA.

5.2 Discussion

The present study recorded the EDA of the subject as an objective physiological response to supplement facial video recordings. It was under the precept that by monitoring autonomic activity through changes in skin conductivity, it would be possible to assess the emotional state of the subject (Vecchiato *et al.*, 2010). Thus, the integration of EDA with self-reports to supplement facial expressions observed would increase the accuracy of confirming the presence of emotion feeling state.

Analysis showed that the average amplitude in the skin conductance response (SCR) reported correlated with facial activity was 0.310µS for amusement and 0.62µS for fear. Amusement yielded a relatively shorter mean rise time of SCR for participants at 3.58 seconds, compared to fear which was greater at 4.40 seconds. This was expected owing to the fact that fear and amusement are considered intensely arousing emotions. Whereas fear stimulates the fight–flight reaction pattern of engagement, characterised by sympathetic activation, involving cardiac acceleration (Van Diest *et al.*, 2009), vasoconstriction, increased EDA, and heart rate (HR) (Globisch *et al.*, 1999; Khalfa *et al.*, 2002; Fernández *et al.*, 2012). Similarly, autonomic physiology of amusement has shown increases in SC level and HR (Khalfa *et al.*, 2002; Robinson & Demaree, 2009).

Moreover, the EDA for the emotional experience of sadness yielded mixed physiological signals than the other aforementioned emotions. This was indicated by the reduction in baseline tonic EDA and absence of a peak for some volunteers whereas SCR was observed in others. As such, it was relatively difficult to precisely reflect emotional changes by using a single physiological signal. One possible causation for lack or low SCR observed may be attributed to the film choice, endorsing a mood state rather than eliciting an emotion. The former differs from emotional states because moods are diffuse affective states that are lower in intensity and longer lasting than emotional states (Mendl *et al.*, 2010; Friedenberg & Silverman, 2015). Velasco and Bond (1998) pointed out the importance of personal relevance on emotional processing. They reported that more personally relevant emotional scripts have resulted in a greater physiological arousal than non-personally relevant scripts. Given that the sadness-inducing film revolved around a theme of a loss, individuals who could not personally identify with the experience of such loss may have not been emotionally engaged to the threshold of arousal and generated a diffuse sad mood state.

EDR was observed in greater proportion of individuals who showed visible signs of distress and crying related behaviours i.e., increased tearfulness, changes in skin colour and vocal sobbing. This supports similar findings in studies that have linked crying-related sadness to increased HR and EDA and greater expression as a result of sympathetic arousal (Gross *et al.*, 1994; Vetrugno *et al.*, 2003).

Furthermore, contradictory findings have been reported with non-crying related sadness with some studies reporting a reduction in HR, SCR, and increased respiration (Gross *et al.*, 1994; Marsh *et al.*, 2008). For example, a study by Marsh *et al*., (2008) which used a clip taken from "*The Champ*" to elicit sadness showed that sad facial expressions in healthy participants were associated with reduced sympathetic and increased parasympathetic activity. While other studies reported increases in HR, and SCR (Ekman *et al.*, 1983), associated with increase sympathetic activity. These studies suggest that different subtypes of sadness are associated with a distinctive physiological pattern which may explain the discrepancy in results (Shirai & Suzuki, 2017).

It also has to be taken into account, that EDA was the sole physiological measure of autonomic activity. Physiological EDA has limitations in the efficacy of assessing emotional states. Owing to that SCR is modulated by sympathetic activity which drives human behaviour, attentional, cognitive, and emotional states on a subconscious level, therefore, may also occur in response to other psychological processes (Figner & Murphy, 2011). Furthermore, various other environmental factors such as temperature fluctuations, and body gross movements have to be considered (Quigley, 2014).

A methodological flaw in the study with the use of EDA, was the absence of electro gel which could impede signal detection and may account for variability in recorded EDA. The inability to generate sufficient skin contact of electrodes may attribute to subjects generating typically low baseline levels (less than 1 µS) compared to other studies (Gross *et al.,* 1994; Marsh *et al*., 2008, Siwan, 2015). This may increase the threshold at which SC would be detected. However, there were some subjects that yielded generally high EDA (16 µS) and subsequently high SCRs. Moreover, it does not explain the decrease in baseline tonic EDA level during the viewing of the sad stimulus which was one of the discrepant findings. Considering the low specificity and accuracy of a single physiological parameter in emotion expression, EDA alone is not sufficient to precisely reflect an emotional arousal state. Where changes in peak SCR accompanied changes in emotional facial expressions for fear and amusement, experiential feelings of sadness could not fully be substantiated. Thus, the presence of experiential and behavioural manifestation of sadness in the absence of SCR could not be ruled out.

Chapter 6 – Results: Facial responses

6.1 Results

Image Extraction

The participants' facial behaviour was analysed during the scenes where subject experienced the target emotion as stated in the self-report questionnaire and recorded as skin conductance changes. This permitted still extraction of facial images representative of the neutral 'baseline' and expressive 'peak emotional response' (Figure 2.2) for each subject from the recorded video footage using video editing software (Adobe Premiere Elements 13). The baseline facial expression was characterised at the neutral positioning of the facial features preceding facial activity movement. The emotional response was considered the apex or the point of greatest excursion. The image views that were extracted for each expression included:

1. The frontal
2. Left profile
3. Right profile

As a result, three image sets consisting of baseline image along with their corresponding emotional state, totalling six images were extracted for each emotional expression captured. As three films were shown to each subject, each with the aim of eliciting one main emotion; sadness, amusement, or fear, this resulted in a total of 426 film viewings. However, not all films successfully elicited the designated emotion, with amusement being the most induced facial emotional response, with fear and sadness induced the least. Aside from this, it was also observed that not all facial expressions could be extracted. In circumstances where extreme body movements or head rotations made it difficult to align facial images to isolate facial activity. Furthermore, not all subjects expressed facial expressions for the desired emotion aimed to be elicited. For instance, "*Lights Out*", elected to be a fear eliciting short film, only elicited fear in 50% of the volunteers. But could only be extracted from 31% of the subjects.

Out of the 426 viewings, 184 emotional facial expressions could be retrieved. Of the 142 participants, image sets were acquired from 111 subjects. The spontaneous expression of amusement was captured for 96 subjects (68% of the subject population) and accounted for 52% of the total appropriated FE. For the emotion of sadness and fear, image sets were derived from 44 subjects (31% of the subject population) and accounted for 24% of appropriate facial expressions. As there were 184 image sets for each of the whole face, profile left and profile right sides of the face, respectively. This resulted in 552 image set (1104 raw images extracted) containing neutral "baseline" and spontaneous emotional response. This can be seen in Table 6.1 which shows the number of subjects for which appropriate facial expressions were captured and processed.

Table 6.1: Image acquired from volunteer responses

	Number of Subjects		
Emotions	**Males (%)**	**Females (%)**	**Total**
Amusement	33(34%)	63 (66%)	96
Sadness	9 (20%)	35 (80%)	44
Fear	7 (16%)	37 (84%)	44

Table 6.1 shows the breakdown of the number of images acquired from a total of 111 volunteers by emotion. Images of amusement were obtained from 96 volunteers. Both sadness and fear from 44 volunteers.

The study revealed that amusement expressions were observed in 34% of male and 66% of female participants. However, when taking into consideration the proportion of male and female participants, 66% of male participants (33/50) and 68% (63/92) of female participants accounted for the expressions of amusement. In contrast, 20% and 80% of male and female made up the expressions of sadness, respectively. This accounted for 18% of total male participants 38% of total female participants. Similarly, 16% of male and 84% of female participants contributed to the expressions of fear. This accounted for 14% (7/50) of total male participants and 40% (37/92) of total female participants. It can be concluded that despite low elicitation of negative emotions of sadness and fear, male and female express positive emotions in equal proportion, however males were less likely to express negative emotions than females. The study demonstrates partial supports that females tend to be more expressive than males, however this was shown only for negative emotions of sadness and fear and cannot be definitive for all negative emotions.

When comparing the number of expressions of participants of Asian and European ancestral background, Asian participants made up 49% and 38% of the participants expressing amusement were European. Furthermore, 59% accounted for the proportion of Asian participants (44/74) and 77% (36/47) accounted for the proportion of persons of European ancestry that participated in the study.

For the expressions of negative emotions, 41% and 43% of sadness expressions were expressed by persons of Asian and European background. Of which 24% accounted for the proportion of Asian participants (18/74) and 40% (19/47) accounted for the proportion of persons of European ancestry that participated in the study. Of the total expressions of fear obtained, persons of Asian and European background each contributed to 45% of expressions of which 27% (20/74) and 43% (20/47) accounted for the proportion of Asian and European participants in the study. It can be deduced that whilst the relative percentages of expressions elicited by person of Asian and European background were similar, as there were more Asian participants than European, people of European background were more likely to express emotions and people of Asian backgrounds were less likely to inhibit emotions. Again, this may be due to the choice and effectiveness of emotional stimuli which cannot be ruled out despite findings of no level of cultural difference in the emotions experienced.

Facial Action Coding of Images

Images of spontaneous FE extracted were coded using FACS (Ekman *et al*., 2002) to determine the extent to which specific AUs are used to portray specific emotions. FACS is a detailed, comprehensive process for describing facial activity by decomposing facial activity into their component of muscle movements or Action Units (AUs) (Ekman *et al*., 2002). FACS consists of 44 AUs, 30 AUs are related to the contractions of specific facial muscles: 12 are for upper face, and 18 are for lower face. The other 14 are referred to as miscellaneous actions (Tian *et al*., 2001). AUs are identified by a number, a shorthand name, and the anatomical basis for its action. Furthermore, the intensity of an Action

Unit is rated on a five-point ordinal scale (A = trace, B = slight, C = marked or pronounced, D = severe or extreme, E = maximum) (Ekman *et al*., 2002).

Coding using the FACS required certified training to learn the individual muscular actions, using the guidelines described by Ekman and Friesen (Ekman *et al*., 2002) to deduce from the signs observed what AUs have contributed to the movement of the skin and other features, and to what intensity.

Regarding spontaneous emotional FE, subjects were coded as showing signs of various expressive behaviours and at various intensity levels. Further combined with the person's individual physical characteristics to produce changes in appearance that vary somewhat across different people. Body and other rigid rotation head movements such as head raising or lowering were often observed which made it difficult to score some muscular activity, which raised uncertainty as to whether some movements may have been prompted by body movement and not the muscular activity itself. Not all FACS codes are based on facial actions. Some provide descriptions of coding situations that are helpful in analysis (Ekman *et al*., 2002), such as AU 25 which denotes that the mouth is open, which could have stemmed from but not definitive of, the occurrence of an activity movement.

Various combinations of AUs were observed for the spontaneous emotional facial behaviour of amusement, sadness, and fear. The intensity of facial movement was scored for 36 AUs (Ekman *et al*., 2002). Up to 7 upper face AUs were observed, 15 lower face AUs, 3 miscellaneous AUs and 6 AUs which describe the head and eye position relative to the camera. The AUs corresponding to emotional facial expressions observed are listed in Table 6.2. Miscellaneous and other action descriptors (ADs) such as e.g., head raising, or lowering were not included but were observed and would be discussed in the later section. Where the total number of possible AUs to appear is 96 for amusement, 44 each for fear and sadness.

Table 6.2: Action Units (AU) observed during emotional expressions

		Frequency		
AU No.	FACS Name	Amuse	Sad	Fear
1	Inner Brow Raiser	2	23	25
2	Outer Brow Raiser	1	1	17
4	Brow Lower		27	17
5	Upper Lid Raiser			25
6	Cheek Raiser	88	3	5
7	Lid Tightener	57	5	17
8	Lip Towards Each Other		1	
9	Nose Wrinkler	2		2
10	Upper Lip Raiser	4	3	3
12	Lip Corner Puller	94	2	
13	Cheek Puffer	2	1	
14	Dimpler		1	
15	Lip Corner Depressor	5	22	15
16	Lip Lower Depressor			5
17	Chin Raiser	1	18	
18	Lip Pucker			1
20	Lip Stretcher		2	16
21	Neck Tightener		1	1
23	Lip Tightener		4	2
24	Lip Pressor	1	5	6
25	Lips Part	51	1	24
26	Jaw Drop Mouth Stretch		1	3
27	Mouth Stretch	4		10
38	Nostril Dilator	4	2	5
39	Nostril Compressor		2	
43	Eyes Closed	1		5

Table 6.2 lists all the AUs observed in subjects during the emotional expressions of amusement, sadness, and fear. The coded AU numbers are arbitrary and do not correspond to any significant value.

Key: AU = Action Unit

Amusement

For the expression of amusement, common AUs scored were AU6, AU7, AU12, and AU 25. AU 12 which acts to pull the lip corners up was the most frequent AU observed and appeared in all but 2 of the subjects, at which AU 13, which raises the lip corners at a sharper angle was observed instead. AU 6 and AU 7 were the most frequently observed upper face AUs and were scored in 88 (92%) and 57 (59%) of the 96 extracted amusement image sets. AU 6 draws the skin from the temple towards the eyes and cheeks due to the contraction of the *orbicularis oculi* muscle, and AU 7 evident in where the eyes are tightened from the raising of lower eyelids and lowering of the upper eyelids. Furthermore, both AUs 6 + 7 often co-occur to narrow the eye aperture and were observed together in 62/96 (65%) amusement expressions. AU 6 + 12 were evident in 76/96 (79%) amusement expressions, the combination of AU 6 + 7 + 12 and AUs 6 + 12 + 25 were seen in 56 (58%) and 44 (46%) of the 96 expressions of amusement. Other AUs observed but less common were AU 9, 13, 15,17, 38 and 64.

Sadness

The most common AUs scored for the expression of sadness included AU 1, 4, 15, and 17. The upper face AUs 4 and 1 were most predominant, occurring in 27 and 23 of the expressive images respectively. AU 1 was evident in the raising of inner corners of the eyebrows, and AU 4 involved in drawing the eyebrows medially and downwards. Furthermore, these AUs co-occurred in 22/44 (50%) sadness expression images. The combinations of the two AUs maintain the raising action of the inner brow from AU 1 with the medial pulling of the eyebrows from AU 4.

AU 15 which illustrated by depression of the corner of the lips was observed in 22/44 (50%) of the facial images. AU 17 caused by the *mentalis* muscle to raise the chin was seen in 18/44 (41%) facial expressions. In a few cases, the combination of AU 15 + 17 together to reshape the lips to a characteristic inverted-U was observed in 8 expressions of sadness. AU 1 + 4 + 15 appeared in 12/44 (27%) image sets, the combination of AU 1 + 4 + 17 scored in 9 (20%) of the 44 expressions.

Additionally, 17 other AUs were also observed at a lesser frequency including 10 lower face AU (AU 8, 10, 12, 13, 14, 20, 23, 24, 25, 26), 3 miscellaneous/ supplementary actions (AU 21, 38, and 39) and 1 action descriptor (AD) (AU 64).

Fear

Regarding facial activity observed for the expression of fear, subjects were coded as showing significantly elevated levels of fearful expressive behaviours. Compared to the expressions of amusement and sadness, a greater number and variety of AUs were scored, especially in the upper face. For example, while one subject scored AUs 1 + 2 + 4

+ 7 + 20 + 25 + 27, another exhibited as many as 9 AUs: 1 + 2 + 4 + 5 + 15 + 16 + 20 + 25 + 27.

AU 1 and 5 were the most frequent AUs observed and appeared in 25/44 (57%) expression images of fear. AU 1 is involved in the raising of inner corners of the eyebrows, and AU 5 elevates the upper eyelid to greater expose the sclera. AU 25 was the second most frequent AU observed. Although the AU reflects separation of the lips, appeared alongside other muscular activity such as AUs 26 and 27 and often co-occurred with AU 20 (responsible for stretching the lips back horizontally) in 11 instances. The upper face AUs 2, 4, and 7 were individually seen in 17/44 (36%) fearful expressions. AU 2 was only present with AU 1 to raise the entire eyebrow and AU 7 and AU 4 co-occurring together in 8/44 (18%) instances. Moreover, the combination of AU 1 + 2 + 5 was seen in 12/44 (27%) expressions. The three AUs acted to raise the entire eyebrows as well as raising the upper eyelid. Another 10 AUs were also observed, including 6 lower face AUs (AU 9, 10, 15, 16, 18, 24), 2 miscellaneous/ supplementary actions (AU 21 and 38) and AU 43.

6.2 Discussion

Cropping

Image pre-processing was manually performed to correctly align images and crop them to uniform pixel size using a photo editing software that was customised for each image analysis. Cropping images was necessary to isolate the activity of interest and ensure reliable reference frames between subsequent images. In order for comparisons between baseline and emotional responses, it was essential for both images to have the same pixel dimensions.

Several issues were encountered when cropping baseline and images of expression to congruent dimensions which impacted on the number of samples that could be analysed. Firstly, the movement of the head within an image sequence was a contributing source of error. Large body movements such as body jolting which affected the position of the head during expressions caused the images to be out of focal plane from one another. These body movements could not be avoided because the study aimed to reflect the real dynamic nature of facial expressions, restricting head movements was not possible and would have impaired natural facial expressions.

More sources of error arose from rigid head movements across and within image sequences. Cohn *et al.* (1999) acknowledged that minor, out of plane rotations adjusted within +/- 5 degrees had no impact on the original dimensions of the captured image. Therefore, images that suffered from head rotations were rotated on a two-dimensional plane of +/- 5 degrees so that face position, size, and orientation were kept relatively constant across subjects, so as to not interfere significantly with feature extraction. Images that required greater degrees of rotation or scaling due to the head being pitched toward or away from the camera were eliminated from analysis.

The second problem encountered was trying to ascertain the same dimensions whilst reducing as much background noise as possible. Though this was only problematic for optical flow analysis where global flow was computed, conservative measures were taken to ensure that only the face was extracted, and as much extraneous background noise was eliminated from the image. Extreme movements associated with eliciting emotional expressions (such as the widening of the mouth when expressing amusement) broadened certain areas of the face. This created issues when images of amusement or fear needed to be cropped for a comparison to a baseline image as both needed to have the same pixel dimensions. Whilst method of cropping was in the order of cropping the image of emotional facial expression first, whereby the features were at maximum length and width, and then followed by assimilating appropriate dimensions for the baseline image accordingly. There was a concern that this would produce 'noise' in the analyses through exposure of some of the background in the baseline images (Lepisk, 2005). This can lead to problems as the optical flow algorithm would have pick up the motion of the background and collate it with all vectors relating to facial activity.

Out of the 142 participants, total of 184 appropriate facial expressions were elicited from 426 short film viewings across 111 subjects. While facial expressions for amusement were successfully induced in 68% of subjects, the two negative emotions, sadness, and fear, were less successful. Facial expressions for these emotions were only elicited in 31% of volunteers. Despite the fact that facial expressions of emotion have signal value, there is little research examining how that signal can be detected under various conditions, because most studies are predominantly based upon near frontal view data. This study obtained image sets consisting of a baseline and peak emotional facial response from three different facial views; the frontal, left and right profile orientations. As each facial expression image set was extracted from each pose variation, this amounted to 552 sets of neutral/baseline and emotional response images (1104 images).

Emotional expression

Despite films possessing relatively remarkable degree of ecological validity (Gross & Levenson, 1995), one concern was the ability of the films to evoke responses congruent to the intended emotions and to the level of behavioural expression. Given the context of the study, how the subject evaluates the films, as having personal meaning or relevance is a major factor as to the nature of the ensuing emotion. Moreover, both affective states and personality traits can shape the perception of a stimulus.

Similar to the perceived emotional experience, emotional responses are partially reflexive, as they can be influenced by conscious modification. Two commonly studied emotion regulatory strategies are cognitive reappraisal and expressive suppression (Gross & John, 2003). Cognitive reappraisal is a form of antecedent-focused emotion regulation strategy which involves reframing emotional events in a way that alters their meanings to change the emotional impact (Mauss *et al.*, 2007; Moore *et al.*, 2008). Expression suppression is a response-focused emotion regulation that entails the management of emotional responses through inhibition or masking to reduce expressive behaviour (Gross, 1998; Gross & John, 2003; Cutuli, 2014).

Studies have shown that reappraisal is effective in minimising the emotional impact of a negative situation (Mauss *et al.*, 2007; Giuliani *et al.*, 2008) and it is a strategy that is frequently used by individuals in everyday life to down-regulate a range of negative emotions. For example, a psychological study by Mauss *et al*., (2007) found that cognitive reappraisal was able to decrease the emotional experience of sadness, disgust, and distress in the absence of significant psychological alterations. Furthermore, individuals who reported more frequent use of reappraisal, particularly with peer interactions generally experienced greater positive and fewer negative emotions (Mauss *et al.*, 2007).

Expressive suppression involves the voluntary management to reduce facial expressions. Unlike reappraisal which alters the course of generated emotions, emotion suppression intervenes once an emotion is underway, thus requiring effort to manage a behavioural response as it arises (Cutuli, 2014).

One concern was the fact that the investigation was conducted with volunteers being aware of the nearby presence of the investigator and knew they were being filmed. As such, the possibility of subjects restraining facial movements due to social and or/ experimental awareness cannot be omitted (Ekman, 1971). Furthermore, the addition of electrode attachment resulted in the hands being placed in an unnatural position during the viewing of the film stimulus. This may have potentially hindered the viewing experience and subsequently compromised the facial behaviour response.

Whilst there were issues regarding voluntary suppression and regulation of facial expressions, ultimately, the greatest concern was to substantiate whether facial expressions of amusement, sadness or fear were actually expressed. When reviewing video footage of subjects, it was often seen that negative emotional responses of sadness and fear were harder to recognise, because facial expressions were visually miniscule. In some cases, no visible changes in facial activity were seen despite volunteers having reported they experienced an emotion. For example, subjects often reported having felt sadness whilst viewing "*Last Minutes with Oden*" but neglected to show any prominent facial changes. The incidence with which an emotion is experienced without necessarily being expressed suggests a certain threshold for an emotional facial expression. This threshold may also be different for each individual.

While it was hypothesised that the use of films would induce discrete emotions it was observed that not all emotions were equally easy to elicit using films. Where the short film stimulus was affective in eliciting amusement in 68% of participants, in contrast, short films were less effective in eliciting expressions of sadness and fear, only eliciting a response in 31% of the 142 subjects.

Given that studies have identified systematic gender differences in facial expressions of emotion, with women appearing more expressive in some emotions than men (Kring & Gordon, 1998; Bailenson *et al.*, 2008). This study revealed that male and female expressed positive emotions in equal proportion, and this was disproportionate in eliciting the negative emotions of sadness and fear where males were less likely to express negative emotions when compared to females. Demonstrating partial support of the fact that females tend to be more expressive than males, however, this only holds true for negative emotions, although sadness and fear are not definitive of all negative emotions.

Furthermore, whilst the relative percentages of expressions elicited by person of Asian and European background were similar, there were more Asian participants. Despite no cultural differences being observed in the level of reported emotions, results indicated that people of European background were more likely to express emotions and people of Asian backgrounds were less likely to exhibit emotions. This may be attributed to the enactment of cultural display rules that have been observed in collectivist groups in Eastern cultures where suppression of emotion is favoured (Matsumoto, 1990). However, due to the limited sample size, in this study this observation is only speculative and warrants further investigation in the future to validate findings.

Facial Responses

To assess reactivity level of sadness, fear, and amusement, expressive behaviour was coded using FACS (Ekman *et al.*, 2002). The methodology involved manual annotation of emotional facial images into anatomically separate and distinguishable facial movements defined as AUs. It is important to note that the study quantified the facial changes that occurred between onset (baseline) and peak of emotional expression. This differed from previous research conducted within in the Unit (Kilincer, 2011, Nguyen 2014; Siwan 2015; Chow *et al.*, 2019) where the baseline images were acquired during the viewing of the blank screen that aired prior to commencement of each short film clip, ensuring a neutral expression was obtained. As such, in this study not all baseline expressions were representative of a neutral response, which is characterised as being devoid of absolute movement. Moreover, the suspected induction of a mood state produced gradual changes in facial configuration which were maintained, this increased the threshold for response changes. Nonetheless, it was hypothesised that the observed facial expression of each emotion consisted of unique facial muscle movements that are distinct from other emotions. As defined by the presence of AUs that adhere to prototypical movement configurations associated with an emotion.

Amusement

The nature of amusement is a correlative response to humour (Sharpe, 1975) where the induction of amusement elicits laughter and increased smiling behaviour. This is observed in typical expressions of amusement which are characterised by raised cheeks [defined by AU 6, cheek raiser] and lip corners [defined by AU 12, lip corner puller] resulting from the contraction of the *orbicularis oculi (pars orbitalis)* and *zygomaticus major*; and parting of the lips [defined by AU 25, lips part] from the relaxation of the *mentalis* or *orbicularis oris* (Ekman & Friesen, 2003; Shiota *et al.*, 2003; Bailenson *et al.*, 2008).

Of the three emotions, spontaneous emotional facial expressions corresponding to amusement were the easiest to identify and more readily observed with the expression generally lasting for a couple of seconds. Consequently, 96 out of 142 (68%) of subjects exhibited facial expressions corresponding to amusement. An example can be seen in Figure 6.1 which depicts the expression of amusement seen in subjects.

Figure 6.1: Facial expression associated with amusement

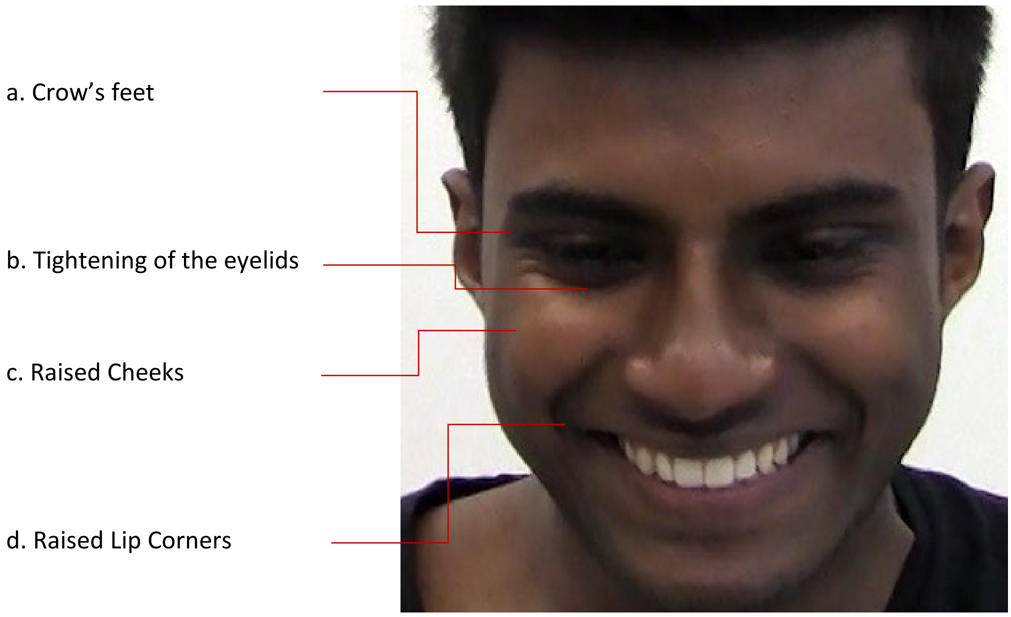


Figure 6.1 is an example of a subject expressing amusement. The characteristic movement seen in subjects included a. raised cheeks, b. tightening of the eyelids, c. marked crow's feet, d. raising of the corners of the lip with mouth open forming a teeth smile. Permission granted for use of this image.

The displays of amusement frequently observed in subjects for the emotional facial expression of amusement included raising of the cheeks (AU 6) which occurred in 96% of expressions, this action is attributed to the contraction of the *orbicularis oculi (pars orbitalis)* which draws the skin from the temple and cheeks, as a result, bags the skin under the lower eyelids causing marked crow's feet or wrinkles to appear at the corner of the eyes (Ekman *et al*., 2002). Furthermore, the relaxation of the upper eyelid and raising of lower eyelids (AU 7) was also observed in 59% of this expression. This action along with AU 6 aids in narrowing the eye aperture, this clustering of AU 6 with 7 manifested in 65% of expressions. Smiling behaviour was a defining characteristic as seen in the stretching of the lips upwards and outwards. AU 12 (lip corner puller) produced these appearance changes in the lips and cheeks due to the contraction of the *zygomaticus major* and was observed in 96% of expressions. Although similar changes can be produced by other AUs such as AU 13 (sharp lip puller) where the *levator anguli oris* draws the corners of the mouth sharply upwards and was observed in 4% of expressions. Additionally, parting of the lips (AU 25) due to the relaxation of the *mentalis* or *orbicularis oris* to expand the smile was detected in 53% of expressions (Ekman & Friesen, 2003; Bailenson *et al.*, 2008). Clustering of AU 12 with 6 was observed in 79% or expressions, AU grouping of 6, 7 and 12 was observed in 58% of expressions, finally AUs 6, 12 and 25 occurred together in 49% of amusement expressions. These changes highly correlate to the prototypical facial configurations of amusement seen in studies (Shiota *et al.*, 2003). The appearance changes in the mouth and eye regions are recognised by most observers as a "Duchenne smile" that reflects signals of a positive inner state (Ekman *et al.*, 1990). Unlike the "non-Duchenne smile" which is considered as a social signal and where appearance changes are only observed in the in the mouth but not the eyes (Gunnery & Ruben, 2016).

In addition to specific facial configurations, there were posture specific patterns executed by subjects during the viewing of the amusement stimulus which included assuming an open body position, leaning back, tilting of the head to the side in a relaxed position.

Sadness

Sadness was the most difficult to identify among the three emotions where only 44 valid facial images were acquired. The nature of sadness, being less arousing and less intense than other emotions, also contributed to recognition difficulty. Display of sadness was typically brief in duration, with minimal to no changes in facial movements despite reports of sadness indicated in the self-report questionnaires. Many subjects displayed slow progressive changes in facial movements. For example, the drooping of the upper eye lid, or maintenance of contraction of the in the inner portion of the eyebrows rather than instantaneous changes in muscular activity as seen in other emotional expressions. This may be reflective of mood dispositions rather than an emotional state.

Recognition of the facial expression of sadness is often associated the inner eyebrows raised, furrowed, and drawn together. These actions are due to the contraction of *Frontalis (pars medialis)* [defined by AU 1, inner brow raiser], and contraction of *corrugator supercilii, depressor supercilii,* and *procerus* [defined by AU 4, brow Lower]; the lips corners are typically depressed from the contraction of the *depressor anguli oris* [defined by AU15, lip corner depressor] which forces the ends of the lips to be drawn laterally and downwards (Ekman & Friesen, 2003; Kohler *et al.*, 2004).

The study revealed that not all subjects displayed all component that make up the prototypical facial behaviour of sadness, but combinations of elements which produced similar appearance changes. These included: inner portion of the eyebrows drawn medially (AU 4), due to contraction of *corrugator supercilii, depressor supercilii and procerus.* This movement was observed in 61% of expressions. The inner eyebrow raising (AU1) through activation of *frontalis (pars medialis)* was seen in 52% of expressions and together with AU 4 which caused horizontal wrinkles to appear at the centre of the forehead. Furthermore, in 50% of sad expressions, mild corner depression of the lips (AU 15) due to action of the *depressor anguli oris* forcing the ends of the lips to be drawn laterally and downwards (Kohler *et al.*, 2004). In other instances, raising of the chin [defined by AU 17, chin raiser] in 41% of expressions from the contraction of *mentalis* further pushing the lower lip upwards causing the appearance of an arc shape of the mouth and mental crease [horizontal groove between the chin and the area below the lips] (Ekman *et al.*, 2002). The clustering of AU 15 and AU 17 was observed in 18% of respondents and additionally, AU 1 and 4 with AU 15 or AU 17 in 27% and 20% of sad expressions, respectively. An example can be seen in Figure 6.2 which depicts facial expression of sadness observed in subjects.

Figure 6.2: Facial expression associated with sadness

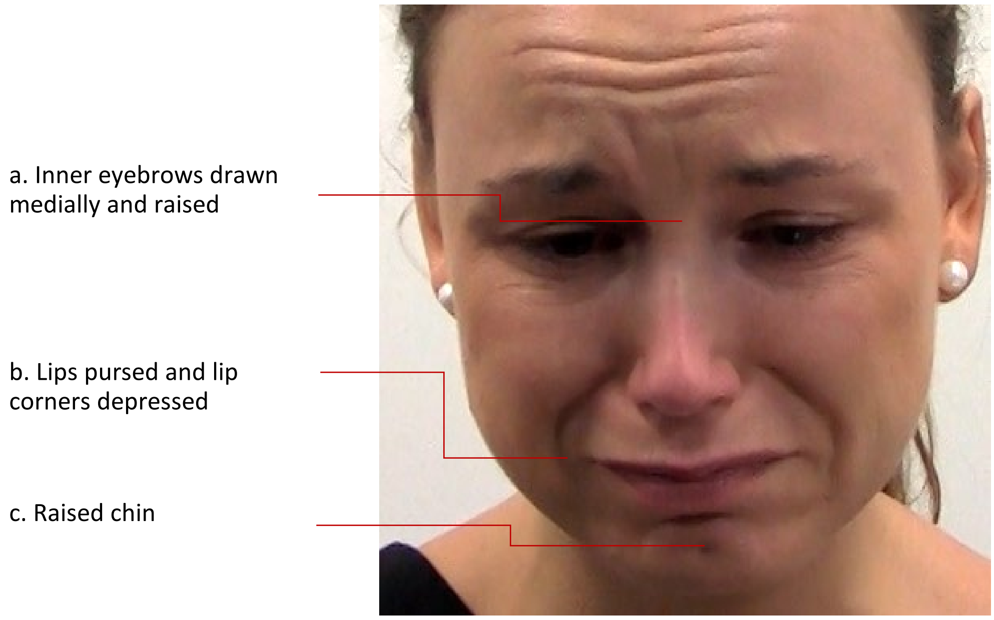


Figure 6.2 is an example of a subject displaying the characteristic expressions for sadness. The movements consist of a. the inner eyebrow drawn medially and raised, b. lips pursed with corner depressed and c. chin raised. Permission granted for use of this image.

In terms of overt bodily behaviour, expressions of sadness were accompanied by closed and slumped body posture, hunched shoulders, and head drooping forward giving the effect of making one appear literally smaller—and by implication in a less threatening stance. Moreover, eyes were casts downwards or looking away, and a loss of focus in the eyes due to the formation of tears.

Several other gestures were observed that were not used for sadness but are worthy of mention, subjects also demonstrated mouth movement as displacement activities which were presented in a wide range of actions such as licking, mouth twisting and biting of the bottom lip which was often pulled inwards. Also, many subjects demonstrated reddening of the face particularly in the malar (cheeks) and orbital areas.

Fear

Similarly, the expression of fear was obtained from only 44 subjects and accounted for 24% of the sets of images that were analysed. Whilst the stimulation of fear is generally accompanied by the presence of a threat (Hammer & Marsh, 2015). The awareness of the surrounding environment might have been enough to dampen expressiveness of fear despite reported feelings of fear.

Recognition of the facial expression of fear is often associated with a raised upper eyelid [defined by AU 5, upper lid raiser] and tensing of the lower eyelids [defined by AU 7, lid tightener] due to contraction of the *levator palpebrae superioris* and *orbicularis oculi (pars palpebralis)*, respectively. The contraction of *frontalis* [AU 1: inner brow raiser, and AU2: outer brow raiser], and contraction of the *corrugator supercilii, depressor supercilii,* and *procerus* [defined by AU 4, brow Lower] to raise and draw the eyebrows medially, while activity of the *risorius* and *platysma* to draw the lips back horizontally [defined by AU 20, lip stretcher] and parting of the mouth [AU: 25 with AU: 26, or AU: 27] (Kohler *et al.*, 2004; Waller *et al.*, 2008).

However, not all of the aforementioned facial activity was observed for the expression of fear, but a combination of AUs which produced similar appearances. Displays of the expressions of fear included: Eyebrow raising (AU 1) and (AU 2) through activation of the *frontalis* which was seen in 57% and 39% of expressions, respectively. The eyebrows pulled together (AU 4) was observed in 39% of expressions and is due to the contraction of the *corrugator supercilii, depressor supercilii,* and *procerus*. The eyes were widened as a result of elevation of the upper eyelids (AU 5) from the contraction of the *levator palpebrae superioris* and tensing of the lower eyelid (AU 7) was observed in 57% and 39% of expressions, respectively. This facial action increases the perceived size of the eye region where the widening of the eyes in states of fear improves the peripheral visual field resulting in greater sensory intake and vigilance (Susskind & Anderson, 2008). Lip and jaw profile changes where lips separated (AU 25), stretched across (AU 20) and opened (AU27) in 55%, 36% and 23% of expressions. The movements are a result relaxation of the *mentalis* or *orbicularis oris* (defined by AU 25, lips part) which part the lips; *pterygoids* with *digastric* muscles which act to lower the mandible and stretch the mouth open (defined by AU 27, mouth stretch) and simultaneous contraction of the *risorius* and *platysma*, which draws the lips back horizontally (defined by AU 20, lip stretcher) (Waller *et al.*, 2008). The clustering of AU 1 and AU 15 was observed in 57% of respondents. Furthermore, AU 1 with 2 and AU 5 was observed in 27% of expressions and AU 20 with AU 25 in 25% of expressions. The expression of the emotion of fear is depicted in Figure 6.3.

Figure 6.3: Facial expression associated with fear

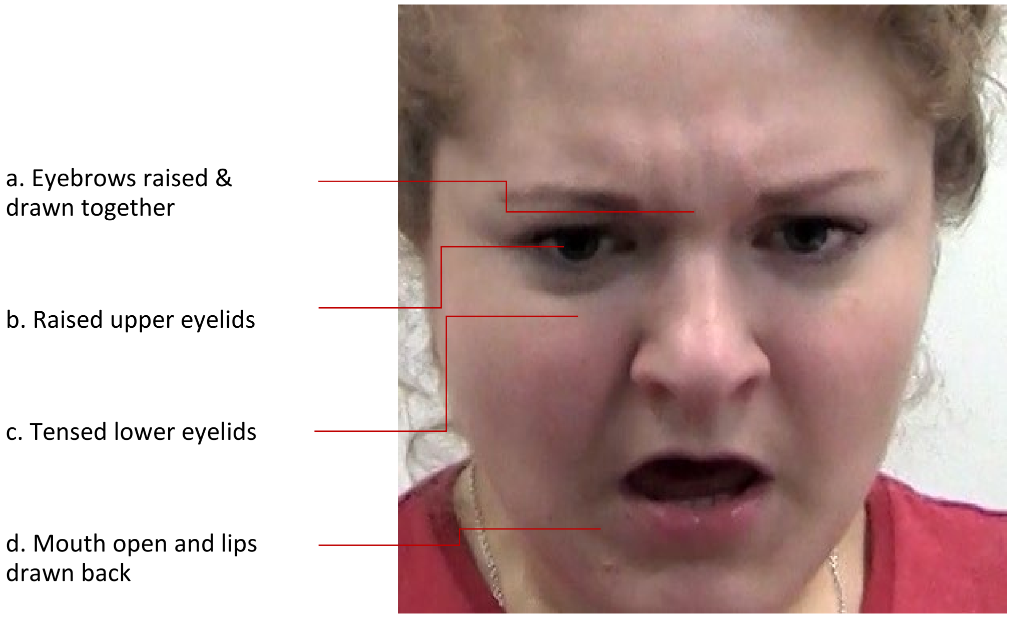


Figure 6.3 is an example of a subject displaying the characteristic expression of fear. Facial movements that include a. eyebrows raised and drawn together, b. raised upper eyelids, c. tensed lower eyelids, and d. mouth open and lips drawn back. Permission granted for use of this image.

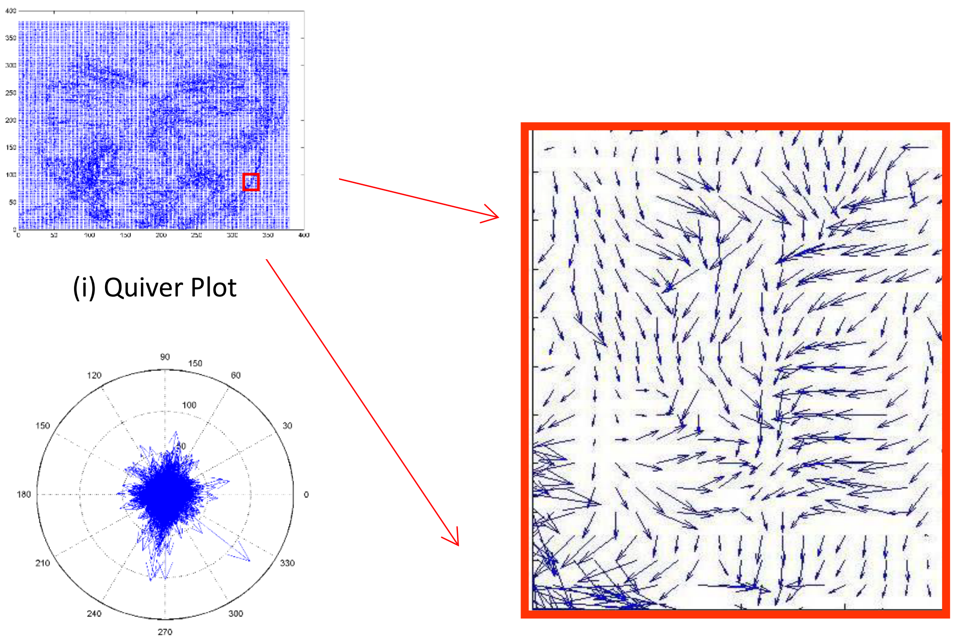
Likewise, expressions of fear were often accompanied by slight backward head movements which cause retraction of the chin, posture adjustments such as straightening of the back, visible deep inhalation. In other instances, avoidance behaviour was observed, where subjects would close their eyes, gaze away from the viewing monitor, or divert their attention elsewhere as to avoid certain scenes. These manifestations were presented during times of discomfort, which were indicated by shifts in body movement. There were also other cases of extreme body movement such as jolting or retreating of the body backwards which caused subsequent changes in head position. This was consistent with previous studies (Chow, 2010; Chow *et al.*, 2019) that reported natural bodily movements that accompanied the expressions.

Chapter 7 – Results: LK optical flow analysis

7.1 Results

For the LK optical flow analysis raw image stills were pre-processed to align images and these were cropped to uniform pixel sizes, 380 x 380 (width x height) pixels and 250 x 380 (width x height) pixels for the frontal and profile facial images, respectively. The optical flow technique was used to compute the global facial activity that occurs between onset and peak of emotional expression. MATLAB (R2017b, version 9.3, USA) implemented an automated version of the LK optical flow algorithm, the script was written by Dr. Budi Jap. MATLAB was used to perform the analysis of facial movement which occurred from the neutral "baseline" image and an emotional response for frontal, profile left and profile right sides of the face. Results were produced in a form of a quiver plot depicting the flow of facial movement as directional vectors. These vectors were rearranged onto compass graphs which mapped the direction of vectors around a 360° plane emanating from a single origin point at the centre of the compass. The compass graph has a bearing range of 0° to 360° running anti-clockwise with respect to the east and is divided into 12 sectors of 30° (see Figure 7.1 (i) and (ii) respectively). The vector angle was determined based on the absolute direction emanating from a central origin point. Figure 7.1 shows an example of an analysis conducted by MATLAB. Where the resulting quiver plot and compass graph constructed from vectors derived from the onset to an amused response for frontal facial orientation for a subject.

Figure 7.1: Optical flow quiver plot and compass graph



(i) Quiver Plot

(ii) Compass Graph

Figure 7.1 displays the output of the LK optical flow analysis. MATLAB deduced vectors which resulted in the facial movement between a neutral "baseline" image and emotional response of amusement. These vectors were plotted onto (i) a quiver plot which depicted the flow of vectors and (ii) a compass graph which re-arranged the vectors from the quiver plot into sectors of 30° on a 360° plane.

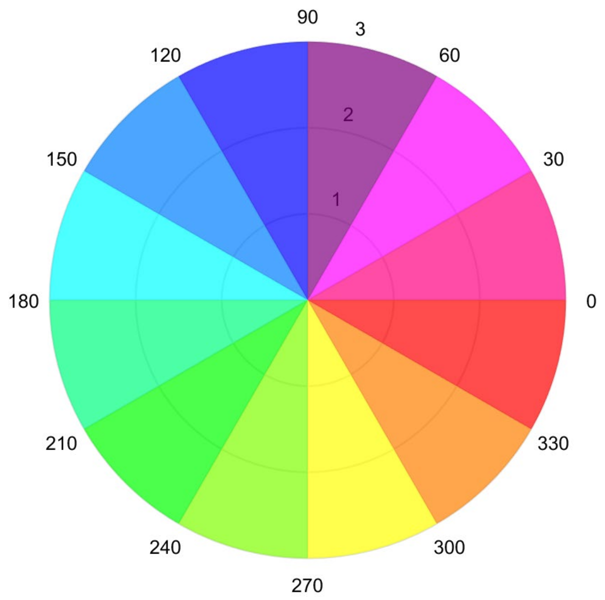
Once the vectors were assigned into sectors on the compass graph, quantified information was deduced from the compass graph for 3 parameters: average magnitude of vectors (pixels); total number of vectors; and average vector angle (degrees). Table 7.1 is an example of the table summary output of the quantified information derived from the image analysis of a subject's expression of amusement from the frontal view. Each 30° sector was designated a colour for quick visual ease of comparison. The average vector magnitude for each sector was considered a feature vector. Figure 7.2 shows a blank compass exhibiting the colour coding for each sector.

Table 7.1: Optical flow data for the frontal facial view registering amusement

	Baseline and Amusement – Frontal											
	Sector 1	Sector 2	Sector 3	Sector 4	Sector 5	Sector 6	Sector 7	Sector 8	Sector 9	Sector 10	Sector 11	Sector 12
Parameter	0° - 30°	30° - 60°	60° - 90°	90° - 120°	120° - 150°	150°- 180°	180° - 210°	210° - 240°	240° - 270°	270° - 300°	300° - 330°	330° - 360°
Magnitude (Pixels)	5.49	6.07	6.51	5.56	4.09	4.15	4.16	4.0	5.48	6.72	5.78	5.82
Total Vectors	15477	16178	21511	17295	9935	8636	6922	6179	8888	11551	10207	11613
Angle (Degrees)	13.57	45.72	75.59	103.26	134.11	165.01	194.05	225.10	256.41	284.83	314.82	345.78

Table 7.1 shows an example of the LK optical flow output for an image analysis of the expression of amusement from the frontal facial view. Once vectors were assigned to a quiver plot and a compass graph, quantified information was deduced. All sectors provided information on three parameters; i) Average vector magnitude (pixels), ii) total number of vectors; and iii) average vector angle (degrees).

Figure 7.2: Colour coding scheme for compass graphs



Sector	Angle	Colour	Sector	Angle	Colour
1	0° - 30°		7	180° - 210°	
2	30° - 60°		8	210° - 240°	
3	60° - 90°		9	240° - 270°	
4	90° - 120°		10	270° - 300°	
5	120° - 150°		11	300° - 330°	
6	150° - 180°		12	330° - 360°	

Figure 7.2 shows a compass graph that is divided into twelve 30° sector with each sector colour coded for visual ease of analysis.

Feature extraction

The parameter of investigation acquired from optical flow analysis was the average magnitude of movement which occurred in facial expressions between the baseline image and peak emotional expression image. This was to observe any differences in the intensity in level of facial movement between emotional responses.

The average vector magnitude values (pixel) were retrieved from each individual analysis and tabulated according to the facial orientation for each emotional expression category.

The mean vector magnitude for the expression of amusement, sadness and fear for the frontal, profile left, and profile right side is summarised in Table 7.2.

Within each emotional category for each facial orientation, the average vector magnitude for each image analysis was manually sorted into one of three groups: Highest, Intermediate, or Lowest. The highest area group consisted of the compass sectors which had attained the four highest average vector magnitude values. The next four highest values were designated into the intermediate group and the compass sectors with lowest four average vector magnitude values were assigned to the lowest group. Each group was denoted by a specific colour for visual ease of comparison. The data was sorted in this manner to detect any consistency in directional movements relative to each subject's range within an emotional facial expression category. Table 7.3 illustrates the sorting of sectors into either one of the 3 groups based on average magnitude values provided by MATLAB (R2017b, version 9.3, USA) for the frontal facial view for the expression of amusement.

Table 7.2: Mean vector magnitudes (pixels)

Average Vector Movements (pixels)													
View	Target Emotion	Sector 1	Sector 2	Sector 3	Sector 4	Sector 5	Sector 6	Sector 7	Sector 8	Sector 9	Sector 10	Sector 11	Sector 12
		0° - 30°	30° - 60°	60° - 90°	90° - 120°	120° - 150°	150° - 180°	180° - 210°	210° - 240°	240° - 270°	270° - 300°	300° - 330°	330° - 360°
Frontal	Amusement	3.32	3.64	4.22	4.1	3.45	3.66	3.89	3.9	4.69	4.67	3.88	3.89
	Sadness	1.71	1.94	2.26	2.29	1.96	2.09	2.19	2.16	2.54	2.46	2.06	2.07
	Fear	3.21	3.64	4.33	4.2	3.43	3.48	3.51	3.47	4.18	4.2	3.57	3.65
Profile Left	Amusement	2.19	2.59	3.02	2.97	2.48	2.6	2.76	2.84	3.38	3.3	2.67	2.65
	Sadness	1.21	1.44	1.66	1.66	1.42	1.46	1.53	1.58	1.82	1.75	1.42	1.43
	Fear	2.38	2.91	3.41	3.35	2.86	2.93	3.08	3.12	3.53	3.39	2.79	2.79
Profile Right	Amusement	2.36	2.69	3.23	3.23	2.76	2.79	2.79	2.84	3.46	3.47	2.92	2.9
	Sadness	1.35	1.57	1.81	1.75	1.49	1.53	1.51	1.51	1.87	1.92	1.66	1.64
	Fear	2.55	2.97	3.52	3.39	2.82	2.83	2.77	2.78	3.35	3.34	2.87	2.94

Table 7.2 displays a summary table for mean vector magnitude for each compass sector for the emotional expression of amusement, sadness, and fear from the frontal, profile left and profile right side.

Table 7.3: Average vector magnitudes for the frontal facial view for the expression of amusement

MAGNITUDE: AVERAGE MOVEMENT OF VECTORS (PIXELS)												
Subject	**0° - 30°**	**30° - 60°**	**60° - 90°**	**90° - 120°**	**120° - 150°**	**150° - 180°**	**180° - 210°**	**210° - 240°**	**240° - 270°**	**270° - 300°**	**300° - 330°**	**330° - 360°**
16001	4.055	4.154	4.638	4.195	3.650	3.961	4.508	4.483	5.012	4.963	4.296	4.383
16002	4.816	5.268	5.959	5.415	4.625	4.933	4.643	4.121	5.140	5.417	4.677	4.869
16004	4.607	4.716	5.459	4.808	4.329	4.445	4.484	4.083	5.069	5.030	4.568	4.874
16006	2.875	3.143	3.907	4.085	3.294	3.619	3.677	3.606	3.903	3.996	3.414	3.332
16007	2.796	3.122	3.486	3.443	3.144	3.305	3.270	3.013	3.292	3.096	2.625	2.848
16008	2.796	3.122	3.486	3.443	3.144	3.305	3.270	3.013	3.292	3.096	2.625	2.848
16010	1.591	1.763	2.089	2.030	1.871	2.203	2.742	2.597	2.820	2.578	2.053	1.999
16011	3.846	4.058	4.532	4.735	4.339	5.026	5.551	5.765	6.479	6.540	5.630	5.180
16012	1.858	2.053	2.534	2.691	2.282	2.452	2.792	2.797	3.050	2.873	2.309	2.298
16013	3.598	3.992	4.380	4.198	3.669	3.595	3.663	3.508	4.198	4.364	3.672	3.857
16014	4.149	4.061	4.442	4.450	3.940	4.554	5.132	5.307	5.913	5.808	4.897	4.815
16015	2.975	3.111	3.601	3.373	2.907	3.199	3.331	3.610	4.430	4.414	3.700	3.583
16016	2.698	3.118	3.656	4.000	3.420	3.429	3.363	3.448	4.033	4.066	3.330	3.313
16017	3.541	4.095	5.554	5.618	4.731	5.107	5.734	5.191	6.001	5.463	4.277	4.150
16018	2.696	2.779	3.012	3.049	2.730	2.962	3.536	3.644	4.389	4.636	3.594	3.475
16019	3.049	3.399	3.702	3.686	3.218	3.315	3.413	3.410	4.021	4.041	3.533	3.755

Table 7.3 reveals how the average vector magnitude for each sector for each expression analysis was manually sorted into one of three groups: Highest; Intermediate; and Lowest. The highest group consisted of the compass sectors yielding the four highest average magnitude values (pixels). The intermediate area group consisted of the compass sector which had the next 4 highest values. The lowest group consisted lowest four compass sector values. Each group was denoted a specific colour for visual ease of comparison of all 12 compass sectors.

Highest Intermediate Lowest

The frequency for each sector with magnitude values falling in the highest, intermediate, and lowest groups was tallied (Table 7.4) and the four most commonly expressed sectors for each level of activity group were transferred onto compass graphs to develop emotion maps. The emotion maps visually illustrate areas of the facial movement that had occurred most often among subjects.

The emotion maps represent the sectors with the highest four frequency mean vector magnitudes belonging to the highest, intermediate, and lowest areas of movement from all expression image analysis. Table 7.4 shows an example of the breakdown of the frequency (%) tallied for each sector. All remaining sector data analysed for vector magnitude for each expression is available in the Appendix. Figure 7.3 is an example of how this data was transferred to develop an emotion map using the compass graph for the frontal facial view signifying areas where facial movement had occurred most often among subjects expressing amusement. The emotion maps are colour coded with sectors emanated from a single point of origin at the centre of the compass map to the length of the mean magnitude value.

Table 7.4a, 7.4b and 7.4c: Frequency tables for average vector magnitudes for the expression of amusement

7.4a Frequency (%) for the highest sectors of movement

Amusement- Frontal- Highest Area of Average Vector Magnitude N=96				
Sector	**Angle**	**Total**	**Subjects (%)**	**Frequency (%)**
1	**0° - 30°**	0	0	0
2	**30° - 60°**	9	9	2
3	**60° - 90°**	60	63	16
4	**90° - 120°**	43	45	11
5	**120° - 150°**	2	2	1
6	**150° - 180°**	10	10	3
7	**180° - 210°**	23	24	6
8	**210° - 240°**	28	29	7
9	**240° - 270°**	86	90	22
10	**270° - 300°**	81	84	21
11	**300° - 330°**	22	23	6
12	**330° - 360°**	20	21	5
TOTAL		384	400	100

7.4b Frequency (%) for the intermediate sectors of movement

Amusement- Frontal- Intermediate Area of Average Vector Magnitude N=96				
Sector	**Angle**	**Total sectors**	**Subjects (%)**	**Frequency (%)**
1	**0° - 30°**	11	11	3
2	**30° - 60°**	35	36	9
3	**60° - 90°**	30	31	8
4	**90° - 120°**	46	48	12
5	**120° - 150°**	24	25	6
6	**150° - 180°**	39	41	10
7	**180° - 210°**	45	47	12
8	**210° - 240°**	39	41	10
9	**240° - 270°**	8	8	2
10	**270° - 300°**	14	15	4
11	**300° - 330°**	44	46	11
12	**330° - 360°**	49	51	13
TOTAL		384	400	100

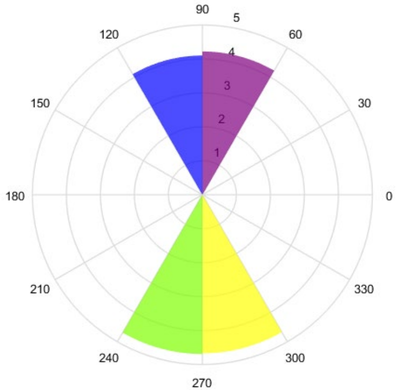
7.4c Frequency (%) for the lowest sectors of movement

Amusement- Frontal- Lowest Area of Average Vector Magnitude N=96				
Sector	**Angle**	**Total sectors**	**Subjects (%)**	**Frequency (%)**
1	**0° - 30°**	85	89	22
2	**30° - 60°**	52	54	14
3	**60° - 90°**	6	6	2
4	**90° - 120°**	7	7	2
5	**120° - 150°**	70	73	18
6	**150° - 180°**	47	49	12
7	**180° - 210°**	28	29	7
8	**210° - 240°**	29	30	8
9	**240° - 270°**	2	2	1
10	**270° - 300°**	1	1	0
11	**300° - 330°**	30	31	8
12	**330° - 360°**	27	28	7
TOTAL		384	400	100

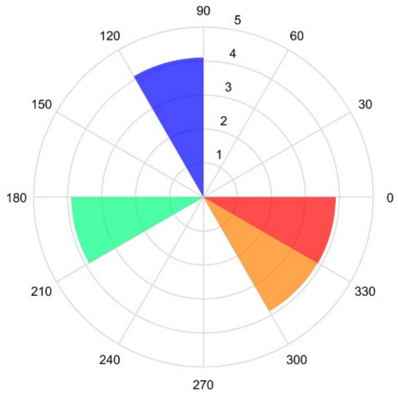
Table 7.4a, 7.4b and 7.4c shows the breakdown of the number of sectors and frequency with which the average magnitude values for each image analysis fell into the 7.4a Highest, 7.4b Intermediate, or 7.4c Lowest area of movement. The sectors expressing the top four frequency values are highlighted with their respective sector colour codes.

Figure 7.3: Emotion maps representing division of movements

i) Amusement - frontal - highest area of movement



ii) Amusement - frontal - intermediate area of movement



Sector	Angle	Colour	Sector	Angle	Colour
1	0° - 30°		7	180° - 210°	
2	30° - 60°		8	210° - 240°	
3	60° - 90°		9	240° - 270°	
4	90° - 120°		10	270° - 300°	
5	120° - 150°		11	300° - 330°	
6	150° - 180°		12	330° - 360°	

iii) Amusement - frontal - lowest area of movement

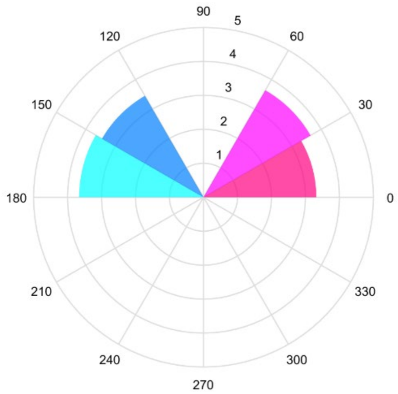


Figure 7.3i), ii) and iii) display the emotion maps representing the divisions of activity most often observed in subjects for the expression of amusement from the frontal facial orientation. The coloured segments represent the four common average feature vector values in the i) higher, ii) intermediate and iii) lower divisions of movement.

Emotion Maps

It is important to note that the emotion maps are used as a visual representation of the feature vectors derived from the optical flow analysis in a way that summarise the various displays of emotional expressions. The emotion maps are an adaptation of the compass graph in that it has a bearing range of 0° to 360° running counterclockwise with respect to the east and is divided into 12 sectors of 30°. The feature vectors corresponding to sectors representing the highest four frequency mean vector magnitudes on the emotion maps are colour coded. The coloured coded sectors extending from the centre point of origin represent both direction and their corresponding mean magnitude value. Furthermore, the emotion maps are not representations of the face where different sectors correlate to different sections of the face. Rather a summation of all directional vectors emanating from the origin of the map.

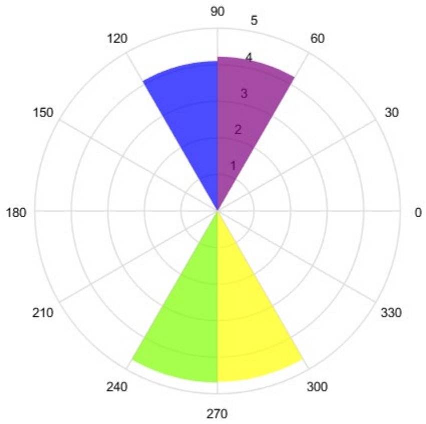
Frontal

The mean vector magnitude for facial expressions of sadness, amusement and fear was analysed across the whole face. The emotion maps in Figure 7.4 represent the sectors which exhibited the greatest frequency of average magnitude values that occurred in either the highest, intermediate, or lowest area groups. This was to illustrate the general degree of movement most often found among the subjects for a particular expression. This was done for all three facial expressions.

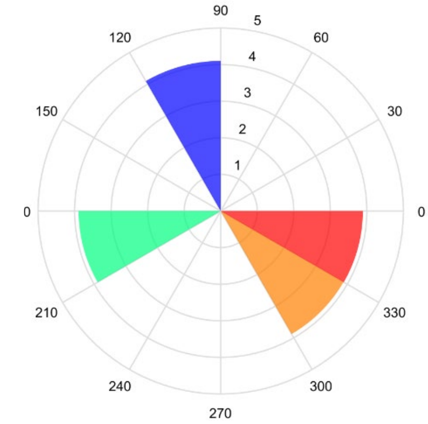
Despite unequal subject numbers for the facial expressions of amusement (N=96), sadness (N=44) and fear (N=44) for the frontal view, similarities rather than differences in appearance of the compass maps were found between these emotion states. All three expressions commonly showed movements in sectors 4, 9 and 10 for the highest areas, sector 12 for intermediate, and sectors 1 and 5 for lowest area of movement.

Facial activity movements that represented the greatest area of movements were directed vertically upwards and downwards however sadness exhibited greater movement directed downwards between sectors 7-10. Difference between facial activity was more apparent clustered into the intermediate group. When comparing the activity for intermediate area of movement, sector 12 was found to be common among all expressions. Sector 4 was prominent in amusement, while sectors 3 and 5 were common in sadness and fear, respectively. Sadness shared sector 11 in common with amusement, and sector 6 with fear. Emotion maps representative of the lowest area of movement were similar between the three emotions with common movements in sectors 1 and 5.

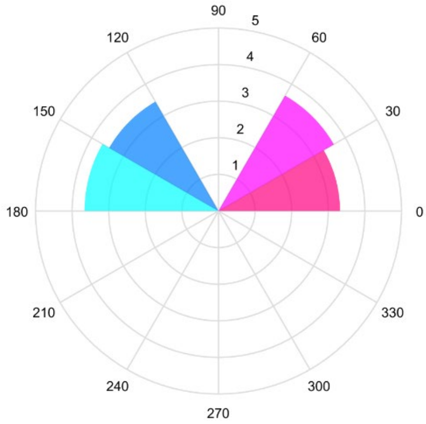
Figure 7.4: Emotion maps of the highest frequency of average vector magnitudes for the frontal facial views



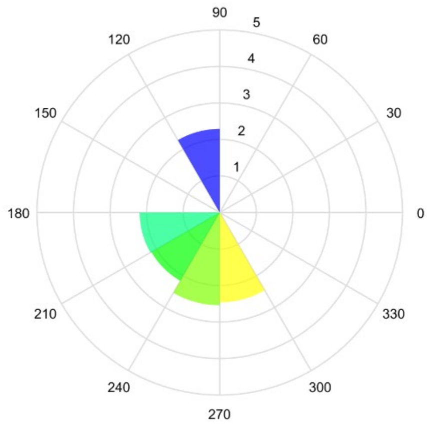
A(i) Amuse - Highest



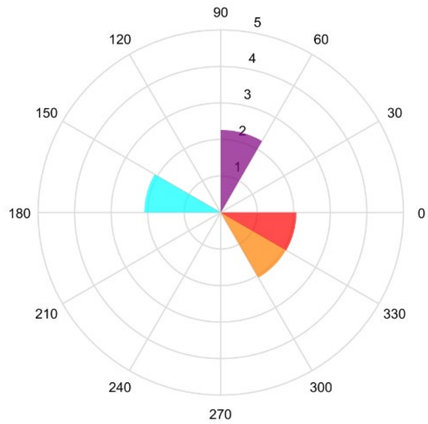
A(ii) Amuse - Intermediate



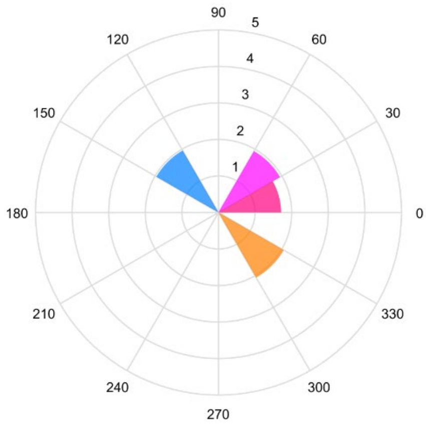
A(iii) Amuse - Lowest



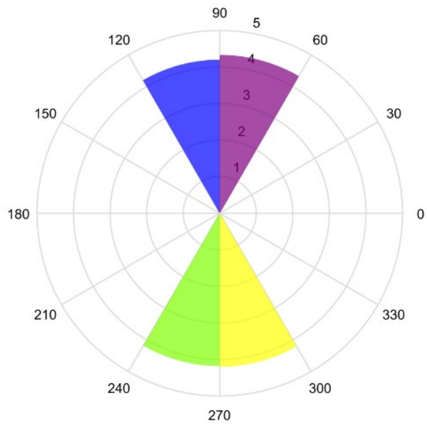
B(i) Sadness - Highest



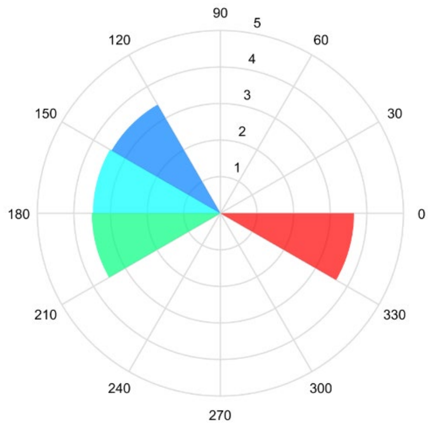
B(ii) Sadness - Intermediate



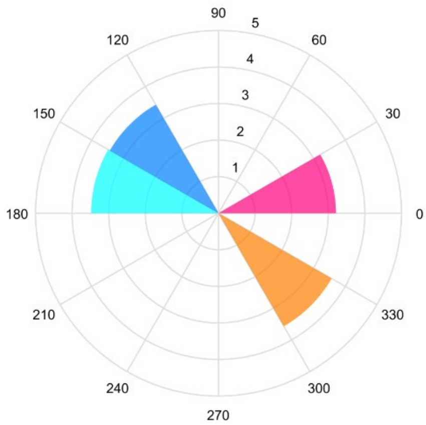
B(iii) Sadness - Lowest



C(i) Fear - Highest



C(ii) Fear - Intermediate



C(iii) Fear - Lowest

Figure 7.4 displays the emotion maps containing colour coded sectors exhibiting the four highest frequency average vector magnitudes for the frontal facial view. Running vertically down the page are emotion maps for (A) amusement, (B) sadness and (C) fear. Running horizontally across the page emotion maps which signify the (i) highest, (ii) intermediate and (iii) lowest areas of movement.

Profile Left

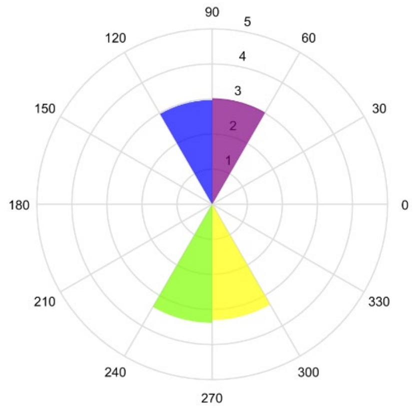
Similar to the analysis of the frontal facial view, emotion maps displayed in Figure 7.5 presents the sectors which exhibited the four highest frequencies of mean vector magnitude values that occurred in the highest, intermediate, or lowest areas of movement. This was done for the facial expressions of amusement, sadness, and fear from the left profile of the face.

It was observed that the expressions differed in intensity levels with lower magnitude of movement from sadness compared to amusement and fear. Visual similarities and difference were observed across all areas of movement, all three expressions exhibited the highest average vector movement with sectors 3, 4, 9, and 10.

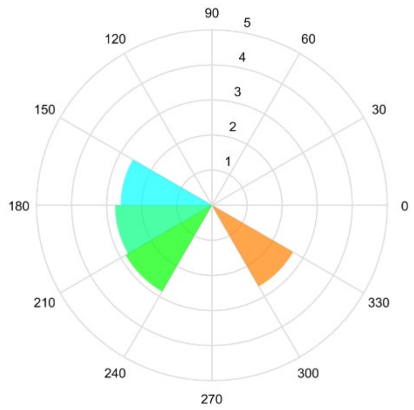
When comparing the activity between the intermediate areas of movement between the 3 expressions, sectors 8 and 11 were commonly exhibited across all expressions. Amusement and sadness were observed to have similar directional movements with greater intermediate activity in amusement. The exception being sector 4 which was seen in fear and sadness, and sector 12 uniquely observed in fear.

A similar trend was observed in lowest area of movement where 3 sectors were commonly found when 2 of the 3 expressions were compared. Sectors 1 and 5 were common across the three expressions. Sectors 11 and 12 were only exhibited in sadness and fear respectively with general movement directed lateral.

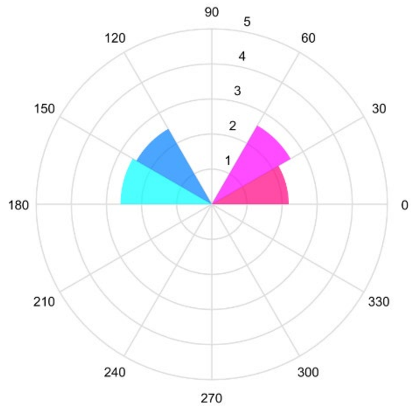
Figure 7.5: Emotion maps of the highest frequency of average vector magnitudes for the left profile facial views



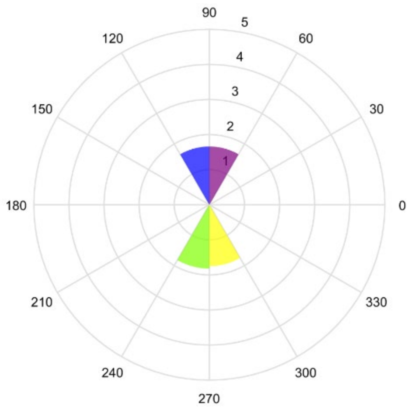
A(i) Amuse - Highest



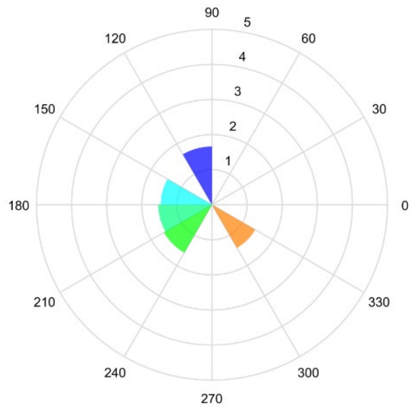
A(ii) Amuse - Intermediate



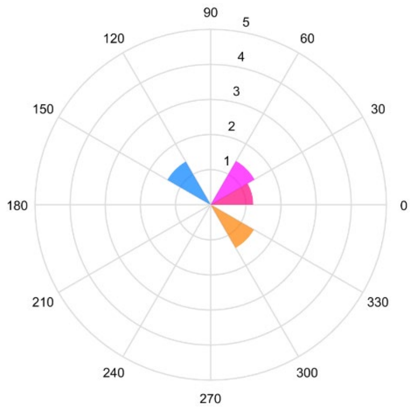
A(iii) Amuse - Lowest



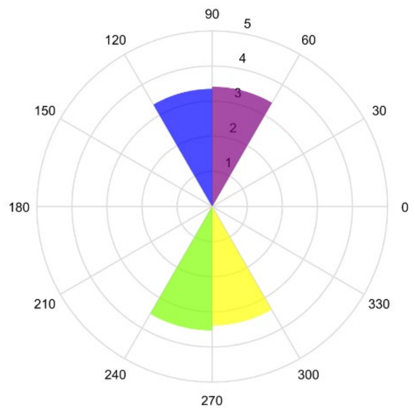
B(i) Sadness - Highest



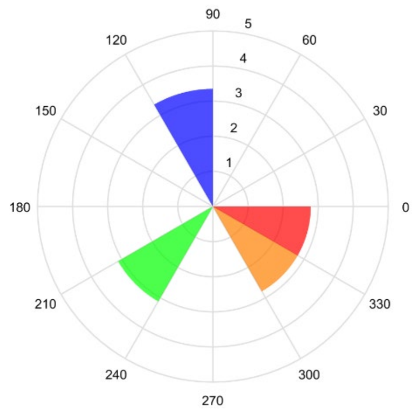
B(ii) Sadness - Intermediate



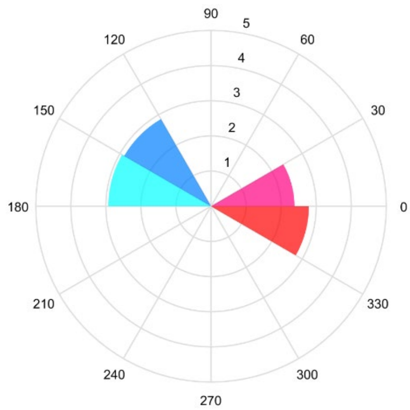
B(iii) Sadness - Lowest



C(i) Fear - Highest



C(ii) Fear - Intermediate



C(iii) Fear - Lowest

Figure 7.5 displays the emotion maps containing colour coded sectors exhibiting the four highest frequency average vector magnitudes for the profile left facial view. Running vertically down the page are emotion maps for (A) amusement, (B) sadness and (C) fear. Running horizontally across the page emotion maps which signify the (i) highest, (ii) intermediate and (iii) lowest areas of movement.

Profile Right

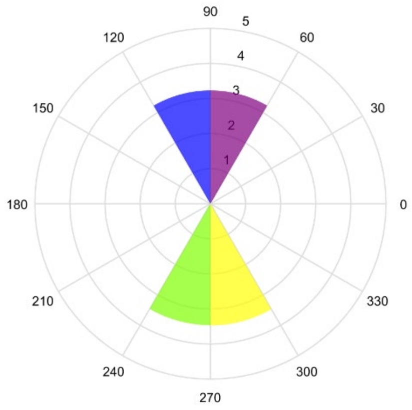
The emotion maps displayed in Figure 7.6 identified the sectors with the four highest frequency of average magnitude values grouped in the highest, intermediate, or lowest areas of movement. This was done for the facial expressions: amusement, sadness, and fear for the right profile of the face.

All three expressions exhibited the highest average vector movement in sectors 3, 4, 9, and 10 but differed in magnitude level with least activity in sadness across all three divisions.

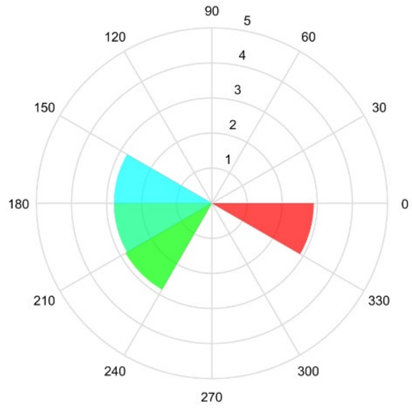
Sectors 6 and 7 were commonly seen across all three expressions in the intermediate average magnitude group. Sector 12 was only observed in amusement, sector 11 was common in sadness and fear, whilst sector 8 was seen in both amusement and fear.

When comparing the activity between the lowest areas of movement across all facial views, amusement and fear exhibited greater mean vector magnitudes. Sectors 1 and 5 were common between all three expressions for the lowest areas of movement.

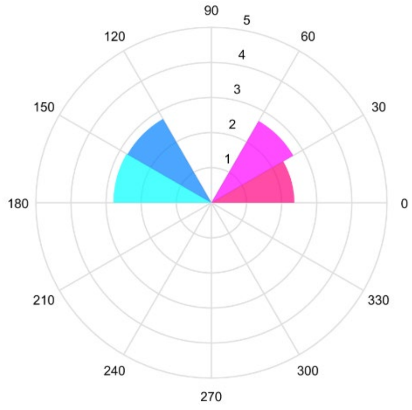
Figure 7.6: Emotion maps of the highest frequency of average vector magnitudes for right profile facial views



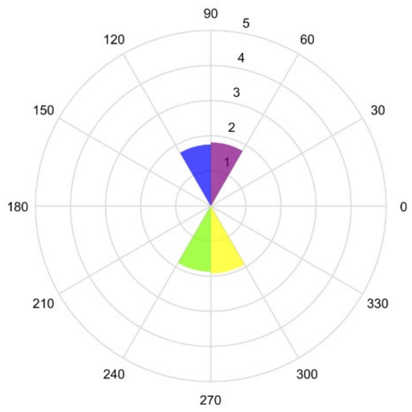
A(i) Amuse - Highest



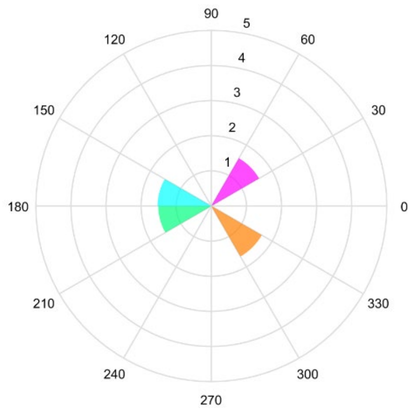
A(ii) Amuse - Intermediate



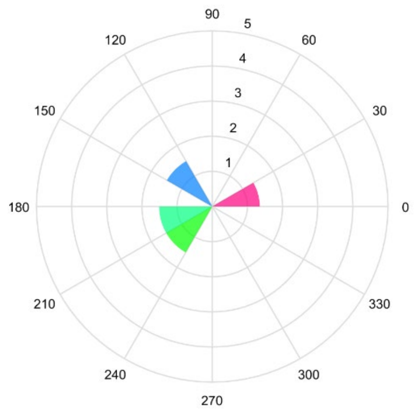
A(iii) Amuse - Lowest



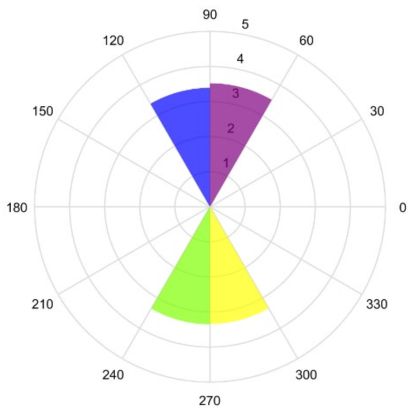
B(i) Sadness - Highest



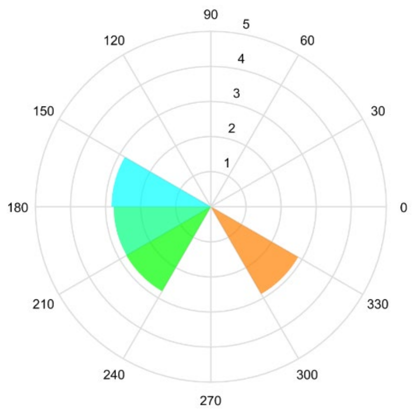
B(ii) Sadness - Intermediate



B(iii) Sadness - Lowest



C(i) Fear - Highest



C(ii) Fear - Intermediate

C(iii) Fear - Lowest

Figure 7.6 displays the emotion maps containing colour coded sectors exhibiting the four highest frequency average vector magnitudes for the profile right facial view. Running vertically down the page are emotion maps for (A) amusement, (B) sadness and (C) fear. Running horizontally across the page emotion maps which signify the (i) highest, (ii) intermediate and (iii) lowest areas of movement.

Classification

Classification for facial expression analysis is the process of categorising facial expressions based on the extracted features (Perveen *et al.*, 2016). The machine learning algorithm uses the measurable properties of a feature to predict to which class an observation belongs. In supervised learning the data set is split into two groups, one dataset with known classes (training set) and the other with unknown classes (validation set) against which the model is tested (Liu & Cocea, 2017; Xu & Goodacre, 2018). The classifiers are trained using the training data to understand how given input variables relate to the class. Once trained, it can be used to make predictions of the testing dataset. To reduce variability, cross-validations are performed by partitioning data into *n* folds (or subsets), followed by an iterative process of combining the folds into different training and test sets (Liu & Cocea, 2017). The validation results are combined over the rounds to estimate a final predictive model.

This study aimed to distinguish among three different emotional facial expression classes, using the feature vectors ascertained from the LK optical flow output as the predictor variable. Classification was executed using the Classification App in MATLAB (R2017b, version 9.3, USA). All 12 feature vectors from each image analysis were uploaded. A variety of classification algorithms were applied to each of the datasets using 5-fold cross-validation to evaluate their performance.

Example of classifiers that were used included:

1. Support Vector Machine (SVM) - which is a supervised learning algorithm that separates data across a decision boundary or hyperplane determined by a subset of data (support vectors) (Kecman, 2005).

2. K-Nearest Neighbors (KNN) classifier technique uses proximity of other classed data points as a proxy for classification. The algorithm checks with 'k' number of nearest neighbors and it assigns a label based on a majority class within the neighbourhood (Harrington, 2012; Spencer *et al.*, 2020).

3. Decision Trees is a structure that splits data points into different categories based on certain conditions that influences decisions.

4. Linear Discriminant Analysis (LDA) is a dimensionality reduction technique which reduces the numbers of variables to describe the data whilst preserving as much of the class discrimination information as possible.

The predictive accuracy was provided by MATLAB (R2017b, version 9.3, USA) to evaluate the performance of each model. Accuracy is an evaluation metric that reflects the percentage of test set samples that are correctly classified by the model (Kotsiantis *et al.*, 2006). For each test sample in this dataset, the known class label is compared with the learned model's class prediction for that sample. Recognition accuracy for the top four of each facial orientation are shown in Table 7.5.

Results reveal that the Support Vector machine (SVM) achieved the highest accuracy of 64% and 67.9% from frontal and left profile sides respectively, followed by the Simple Tree classifier (frontal = 61.4%; left profile = 66.3%) and the LDA achieving the lowest accuracy score. The Simple Tree classifier achieved the highest accuracy percentage score of 67.9% for the right profile side, followed by SVM at 66.8%, the KNN model yielded the least accuracy percentage score of 62.5%. Classifiers achieved higher recognition accuracy for the left and right profile sides compared to frontal facial orientation.

Table 7.5: Overall recognition accuracy of classifiers for emotional facial expressions

		Recognition Accuracy Percentage (%)			
Optical Flow		SVM	KNN	SIMPLE TREE	LDA
	Front	**64.0**	59.2	61.4	53.8
	Left	**67.9**	66.3	66.3	62.0
	Right	66.8	62.5	**67.9**	64.7

Table 7.5 shows a comparison of performance for the top four classifiers using optical flow data based on accuracy (%) as a metrics for evaluating the true class. Where the classifiers with the highest accuracy score (%) for each facial view is highlighted in green.

Key: SVM = Support Vector Machine; LDA = Linear Discriminant Analysis; KNN = K- Nearest Neighbors

Further insight as to the performance of a classification algorithm can be drawn from confusion matrices which describes how well the classifier performed for each class. The confusion matrix provides a breakdown of the classification rates of the individual expression type by class and compares the model's predicted class values to the actual class values (Spencer *et al.*, 2020). In a confusion matrix table, each row of the matrix corresponds an actual class and each column of the matrix corresponds to a predicted class. The principal diagonal cells show where the true class and predicted class match revealing how many samples in that class have been classified correctly. Confusion matrices for the highest performing model for the frontal, profile left, and right sides are shown in Tables 7.6 where each column represents a predicted class and row represents the true classes to which the expression belongs. Correct predictions run along the principal diagonal highlighted in green.

Confusion matrix of the SVM classifier for the frontal facial expressions shows that when 96 amusement expressions were presented, the SVM classified 88 (92%) expressions as amusement and misclassified 8 expressions as sadness. Furthermore, the amusement expression was predicted for 132 cases, therefore amusement expression accounted for 67% of correct predictions. When 44 sad expressions were presented, the SVM correctly classified 30 (68%) cases as sadness whilst the remaining 14 (32%) cases were misclassified as amusement. Moreover, sadness accounted for 58% of the 52 predictions of sadness. Another important finding was that the model failed to recognise or predict fear expressions.

Similarly, for the profile sides, the confusion matrix of the SVM classifier for the left profile side showed that 91/96 (95%) amusement were correctly classified and accounted for 69% of the total predicted (131) amusement expressions. Compared with sadness where 32 out of possible 44 expressions of sadness (73%) were correctly classed, making up 64% of the 50 images predicted for sadness expression. Only 2 of 44 fear images were detected (5%) which accounted for 66% of the predictions of fear.

Confusion matrix of the Simple Tree classifier for the right profile side showed that majority of predicted expressions belonged to amusement in which 86/96 (90%) were correctly classified. Moreover, 124 expressions were predicted as being an amusement expression, of which 69% were correctly predicted, whilst 30/44 (68%) of sadness expressions were correctly classed and 67% were correctly predicted. Recognition of fear had slightly improved with 9 (20%) of the 44 fear expressions detected and made up 60% of correct predictions.

Table 7.6c, 7.6b and 7.6c: Confusion matrices for the best performing classifiers for the frontal, left and right profile facial views

Table 7.6a Confusion matrix for the frontal facial view using the SVM classifier

True Classes	Class	Predicted Image Classes		
		Amuse	Sad	Fear
	Amuse	88	8	0
	Sad	14	30	0
	Fear	30	14	0

Table 7.6b Confusion matrix for the left profile view using the SVM Classifier

True Classes	Class	Predicted Image Classes		
		Amuse	Sad	Fear
	Amuse	91	4	1
	Sad	12	32	0
	Fear	28	14	2

Table 7.6c Confusion matrix for the right profile view using a Simple Tree Classifier

True Classes	Class	Predicted Image Classes		
		Amuse	Sad	Fear
	Amuse	86	4	6
	Sad	14	30	0
	Fear	24	11	9

Tables 7.6a, b and c display a series of confusion matrices which explain the breakdown in recognition of the images of three emotional facial expressions: amusement, sadness and fear. The number of expression images that were correctly classified runs along the principal diagonal indicated by green shaded boxes.

Key: Amuse = Amusement; SVM = Support Vector Machine

Apart from accuracy, the confusion matrix can be utilised for calculating other performance measure evaluation metrics such as precision, recall, and F_1 measure, all defined as follows:

Precision refers to the proportion of correctly classified positive predicted outcomes e.g., for all the predicted amusement expressions, how many were correctly identified. It is defined as the number of true positives (TP) divided by the number of true positives (TP) plus the number of false positives (FP):

Precision = TP/(TP+FP)

Where TP is given by the number that were correctly classified and FP are cases in which the model incorrectly labels an expression as belonging to the said emotional category where it does not belong. For example, the FP prediction of amusement would label an expression as amusement when it was actually sadness.

Recall is the proportion of positive cases that are correctly classified as being positive e.g., of the 44 fear expressions, the number were classified as fear. It is given by the number of TP divided by the number TP plus the number of false negatives (FN). Where FN refers to the number samples in the expression category which were not classified correctly by the model.

Recall = TP/ (TP +FN).

While recall expresses the ability to find all relevant instances in a dataset, precision describes the proportion of the data points the model says were actually relevant.

The F_1 measure or score summarises the model's performance by combining the harmonic mean of precision and recall (Sasaki, 2007; Bailenson *et al.*, 2008). The F_1 measure is computed as a simple arithmetic mean of per-class F_1 and given by:

F_1 measure = 2* Precision x Recall/ Precision + Recall

Where the F_1 measure is valued between 1 indicating perfect precision and recall, and 0, which may be due to either the precision or the recall being zero. In the case of an uneven class distribution, a weighted-average F_1 measure can be used to evaluate the accuracy of the classifier model. This is computed by weighing the F_1 measure of each class by the number of samples from that class (Shmueli, 2019). In this case, yielded a total of 184 samples: 96 amuse, 44 each for sadness and fear. The weighted F_1 measure is thus computed as follows:

$$\textbf{Weighted-}F_1 = \frac{N(\text{amuse}) \times F_1(\text{amuse}) + N(\text{fear}) \times F_1(\text{fear}) + N(\text{sad}) \times F_1(\text{sad})}{N \text{ total samples}}$$

The weighted-F_1 measure was calculated for the Support Vector Machine (SVM) classifier for the frontal facial orientation, and the left profile side, and Simple Tree classifier for the right profile side. Similarly, weighted precision and weighted recall was also computed. The results are summarised on Table 7.7 displaying the number of TN, FP, FN and TN classification for each expression class as well as the precision, recall and F_1 measure which were converted and displayed as a percentage value (%).

The F_1 measure was lower than the initial recognition accuracy which is equivalent to the weighted recall. The SVM classifier for frontal facial orientation yielded a weighted F_1 measure of 55.22% compared to accuracy at 64.13%, which may have been impacted by the 0 recognition of fear. The right profile side with the Simple Tree classifier model achieved the highest recall with 67.93%, highest weighted F_1 measure of 64.21%. Whereas the left profile side achieved a lower weighted F_1 measure of 60.15% despite achieving a high precision of 67.49% and higher recall 67.93%.

Table 7.7a, 7.7b and 7.7c: Performance summary of classifiers for the frontal, left and right profile facial views

Table 7.7a SVM Classifier Summary for the frontal facial orientation

	Number of expressions						
Class	TP	FP	FN	TN	Precision (%)	Recall (%)	F_1 measure (%)
Amuse	88	44	8	44	66.67	91.67	77.19
Sad	30	22	14	118	57.69	68.18	62.50
Fear	0	0	44	140	0.00	0.00	0.00
Weight Average					48.58	64.13	55.22

Table 7.7b SVM classifier Summary for the left profile view

	Number of expressions						
Class	TP	FP	FN	TN	Precision (%)	Recall (%)	F_1 measure (%)
Amuse	91	40	5	48	69.47	94.79	80.18
Sad	32	18	12	122	64.00	72.73	68.09
Fear	2	1	42	139	66.67	4.55	8.51
Weight Average					67.49	67.93	60.15

Table 7.7c Simple Tree classifier Summary for the right profile view

	Number of expressions						
Class	TP	FP	FN	TN	Precision (%)	Recall (%)	F_1 measure (%)
Amuse	86	38	10	50	69.35	89.58	78.18
Sad	30	15	14	125	66.67	68.18	67.42
Fear	9	6	35	134	60.00	20.45	30.51
Weight Average					66.47	67.93	64.21

Tables 7.7a, b and c summarise the number of expressions that were considered true negative, false positive, false negative, true negative. Furthermore, the precision, recall and F_1 measure (%) for 7.7a Support Vector Machine (SVM) classifier for the frontal facial orientation, 7.7b Support Vector Machine (SVM) classifier for the left profile side and 7.7c Simple Tree classifier for the right profile side.

Key: Amuse = Amusement; SVM = Support Vector Machine; TP = True Positive; FP = False Positive; FN = False Negative; TN = True Negative

7.2 Discussion

Emotion maps

The purpose of using computer vision techniques when applied to images was to extract motion facial activity using pixels movements in the form of feature vectors representing the displacement (pixels) and direction (degrees) of changes occurring on the face. Emotion maps were created in the form of compass graphs which display feature vectors as arrows emanating from the centre origin. The emotion map has a bearing range of 0° to 360° running anti-clockwise with respect to the east. The purpose of the emotion maps was to illustrate the overall directional area of movement that was most often seen in the subjects for the emotional expression of amusement, sadness or fear. Thereby highlighting any patterns and trends that may differentiate the three emotional facial expressions from invariant poses. It was anticipated that observed trends would be applied to expanding the work towards automating detection of facial expressions of affective states (Chow, 2010; Siwan, 2015; Sidavong *et al.*, 2019; Chow *et al.,* 2019).

Optical flow when applied to images to extract global facial activity, depicted motion flow in the form of vectors. Feature vectors were generated by interpreting vector magnitude of the frontal, left, and right profile facial views between the three expressions and how they acted within 12 sectors of a 360˚degree circular plane compass graph.

A limitation of feature vectors generated by the LK optical flow algorithm was that they do not represent facial activity in accordance with various regions of the face (such that the left part of the compass doesn't represent the left side of the face, nor the right side of the compass graph represent the right side of the face). Rather it is a summation of all directional vectors emanating from the origin of the graph. The depiction of expression in this manner posed an issue for facial expression analysis in that, by summing all direction flow onto compass segments, made it difficult discern which facial features contributed towards the expression. This trend was also observed in previous studies (Chow, 2010; Nguyen 2014; Chow *et al*., 2019) when the average vector magnitude and their corresponding compass sectors were mapped, this could not distinguish between the three expressions. Chow (2010) acknowledged that the analysis on vector angle was hindered by the application of the algorithm, due to this summation of vectors. However, none of their feature vectors were presented as inputs into classifiers.

Previous research in Predictive Imaging Unit at UTS (Duthoit *et al*., 2008; Chow, 2010; Kilincer, 2011; Chow *et al*., 2019), utilised only a subset of data, being the highest average magnitude values. Incidentally, the combination of the movements of AUs that make up discrete facial expressions yielded similar directional movement (Chow, 2010; Nguyen, 2014; Chow *et al*., 2019). Visual analysis involved mapping feature vectors of facial expression activity onto emotion maps according to the level of activity (Siwan, 2015). Feature vectors for each subject were sorted into descending order of magnitude and allocated into one of three groups representing divisions of higher, moderate, or lower facial activity.

The highest average vector magnitude reflects the directions with which movements in the face were highly innervated. The intermediate areas of movement reflect the collective movements of areas of the face that are moderately innervated and lowest areas of movement represent the directions with which minimal motions were detected. By grouping them in this manner it was hoped would clarify any similarities or highlight subtle differences in facial motion that may have occurred between different emotional expressions.

It was also assumed that emotion maps representative of highest area of movement were influenced by summation of directional movements of AUs that make up the expression and will be further discussed below (Chow, 2010; Chow *et al*., 2019). No inferences could be made as to what particular movements of facial features accounts for intermediate and smallest areas of movements. Therefore, they could only be used to supplement findings of highest activity of movement to reinforce any similarities or differences observed between expressions (Chow, 2010; Siwan, 2015; Chow *et al*., 2019).

Despite the observable physical facial differences between emotional expressions, similarities in the directions of movement were found when mapping the highest average vector magnitudes for the frontal and profile facial views across the expressions: amusement, sadness, and fear. Furthermore, emotion maps did not vary in distribution of global flow vectors between the left and right profile sides. The compass graphs exhibited common movements in sectors 3, 4, 9 and 10 for all three emotional expressions for the different facial orientations, with the exception of the expression of sadness for the frontal facial view. These sectors relate to the summation of vector movements that occurred within 60˚ to 120˚ and 240˚ to 270˚ degrees with respect to the origin which are primarily directed upwards and downwards along a vertical plane. Slight variance in distribution of global vectors between emotional expressions from the frontal facial view may suggest marginal discrimination potential for sadness. Where the emotional expressions of sadness did not share common average vector movement in sector 3 (60˚ to 90˚) but instead differed in movements in sectors 7-8 (180˚ to 240˚) (refer to Figure 7.4).

With respect to the origin, vertical movements for amusement were a consequence of the concurrent contraction of the *zygomaticus major*, causing the lip corners to stretch upwards and outwards (defined by AU 12, lip corner puller) and as a result, causing the downward depression of the lower lip. This was further heightened due by the relaxation of the *mentalis* or *orbicularis oris* [defined by AU 25, lips part], forcing the bottom lip to depress downwards to form a 'teeth smile' (Root & Stephens, 2003; Waller *et al.*, 2008). Likewise, contraction of the *orbicularis oculi*, with the orbital portion causing rising of the cheeks [defined by AU 6, cheek raiser], and the palpebral portion creating tension and the downward movement of the upper eyelid and elevation of lower eyelids [defined by AU 7, lid tightener], causing the eyelids to become closer.

The summation of vector movements along the vertical plane upwards for the expression of sadness was a consequence of the simultaneous contractions of the *depressor anguli oris* [defined by AU 15, lip corner depressor], and *mentalis* [defined by AU 17, chin raiser] causing lateral inferior stretching of the lips whilst pushing the lower lip upwards. Furthermore, the contraction of *corrugator supercilii, depressor supercilii* and *procerus,* which draws the eyebrows medially and downwards [defined by AU 4, brow lower], and the contraction of *frontalis (pars medialis)* [defined by AU 1, inner brow raiser] which resulted in the upwards movement of the inner eyebrows (Ekman *et al.*, 2002).

Summation of movements for the expression of fear was a result of the relaxation of the *mentalis* or *orbicularis oris*, causing the lips to part [defined by AU 25, lips part], and simultaneous contraction of the *risorius* and *platysma*, causing the lips to stretch laterally [defined by AU 20, lip stretcher]. The contraction of the *levator palpebrae superioris*, responsible for elevating the upper eyelids [defined by AU 5, upper lid raiser] (Ekman *et al.*, 2002; Waller *et al.*, 2008) and contraction of the *orbicularis oculi*, causing downwards and lateral tension beneath the lower eyelids [defined by AU 7, lid tightener]. While the contractions of the *corrugator supercilii, depressor supercilii* and *procerus* drew the eyebrows medially and downwards [defined by AU 4, brow lower]. Finally, the contraction of *frontalis* [defined by AU 1, inner brow raiser, and AU 2, outer brow raiser] which acted to raise the eyebrows (Ekman *et al.*, 2002).

Visual inspection of emotion maps representative of intermediate and lower activity for all three emotions showed greater variations in distribution of sectors. When observing the intermediate area of movement, movement in the direction towards 330° to 360° (sector 12) was only common for all three facial expressions for the frontal facial orientations. Movement in the direction of 210° to 240° and 300° to 330° (sectors 8 and 11) for the left profile side, and 150° to 210° (sectors 6 and 7) for the right profile side. Common sectors exhibited by all three emotions for the lowest areas of movement included movements towards the direction of 0° to 30° and 120° to 150° (sectors 1 and 5) for the three different facial orientations. This suggested that the discrimination between the three emotions is more apparent in active segments relating to moderate and minimal areas of facial activity. This may play a role in discrimination when used as features vectors for classification.

Having observed the emotion maps representative of average vector movements for the expressions of amusement, sadness, and fear within different facial views, visual similarities were observed between the frontal views and profile views when observing the highest area of movements. Meaning that despite different facial expression being caused by the innervation of different muscle activity groups, the summation of these movements did not vary from one another to differentiate each emotion. However, differences became apparent when the intermediate and lowest areas of movement are taken into consideration. This may be attributed to the action of large, dominant facial muscles on the lesser muscles or by independent mimetic movements of muscles characteristic to each emotion. Therefore, no inferences could be made as to what particular movements of facial features accounts for intermediate and smallest areas of movements. This may be a limitation of the utility of the optical flow algorithm.

In general, greater activity was observed from emotion maps in frontal compared to profile views across the three emotional expressions which indicates deviations from frontal views affected visibility of movement. This was expected due to the decrease in visibility of the morphological changes that occur on the surface of the face when represented in profile. Furthermore, fear yielded overall greater intensity of movement and sadness the least intensity. Two possible explanations may be that in general given that amusements and fear are high arousing emotions involving displacement from oral movements which may account for a large proportion of vector movements. Another possibility could be difficulty in activation of sadness from the baseline. Which may dampen expression behaviour. Nonetheless, having investigated the average vector magnitude across the whole face, right and left profile, it was concluded that this parameter would not have the sensitivity to appropriately detect differences in facial expressions.

Classification

In this study the feature vectors obtained from the LK optical flow were used to see whether the patterns of activity could be used to classify emotions. Feature extraction is a core component of the computer vision pipeline which works around the idea of extracting useful features which define the objects in the image. The input feature properties are a measurable piece of data which is unique to this specific object. Selection of a good feature can lessen the within-class variations and maximise between-class variations of emotions, thereby increase the predictive power of the machine learning algorithm (Samadiani *et al.*, 2019).

Whilst expression classification works reasonably well for posed expressions, spontaneous or naturally occurring expressions are typically much more difficult to recognise. This has been demonstrated in works by Bartlett *et al.* (2006) who employed a trained recogniser of AUs using the FACS system on two data sets (CK and Ekman-Hager) of posed expressions and a database of spontaneous facial behaviour (RU-FACS data set), showed that recognition performance on the spontaneous database dropped by 20%. As such, it was expected that recognition of naturally occurring emotions would be more difficult than recognition of posed emotional facial expressions or those expressed on command.

Classification was performed on the obtained feature vectors acquired from the LK optical flow analysis. As emotional facial expressions have demonstrated specific facial muscle patterns (Keltner & Buswell, 1997; Kohler *et al.*, 2004; Waller *et al.*, 2008) it was hypothesised that spontaneous facial expressions of basic emotions could be differentiated using computer vision analysis, from frontal and profile (non-frontal) views. A study by Moore *et al*. (2009) explored the effects of pose variation on facial expression recognition. The study utilised images from the Binghamton University 3D Facial Expression (BU-3DFE) database using Local Binary Patterns (LPB) to characterise facial expressions over 5 yaw rotation angles from frontal to profile views and SVM classification. Results revealed that although the frontal pose is the optimal view, performance does not decrease significantly due to yaw variation. Hence, it was predicted that recognition accuracy when viewing faces in profile would be lower than recognition accuracy of the same faces from the front facial view.

The baseline metric used included weighted F_1 measure, recall and precision scores to evaluate the model to measure the accuracy of a classifier in the context of imbalanced data. Using feature vectors obtained from the LK optical flow analysis, the best result for emotion classification was achieved by the SVM and Simple Tree classifiers for the left and right profile views with an accuracy recognition of 67.9% compared to the frontal facial view which achieving 64% recognition accuracy using the SVM classifier. Furthermore, the left and right profile yielded similar 67% and 66 % precision and 49% for frontal, and F_1 measure was greatest for right profile at 64%, profile left at 60% and 55% for frontal. Surprisingly, recognition was not negatively affected when viewed from the profile sides. In fact, they improved with the profile right facial views obtaining the best recognition and frontal facial views obtained lowest recognition across the board for precision, recall and overall F_1 measures. Which goes against the initial prediction that that frontal view is optimal for overall expression recognition (Moore *et al.*, 2009). It is possible that invariant poses may highlight areas not captured in the frontal facial orientation that might be of relevance and may be advantageous when differentiating between emotional expressions.

Despite achieving reasonable recognition rates, classification of individual emotions showed that recognition of amusement was much greater in comparison to the recognition of fear and sadness, which may have affected the overall accuracy rate. Recognition of fear was remarkably poor, in fact it was not detected at the frontal and with a slight improvement from the profile right view. The results of this study confirm previous findings that the implementation of the LK optical flow algorithm worked poorly for spontaneous emotional facial expressions (Chow, 2010; Kilincer, 2012; Nguyen, 2014; Siwan, 2015; Chow *et al*., 2019). Given the subtle nature of expressions, the summation of overall motion as computed by the optical flow algorithm produced weak features. Both observational analysis of emotion maps and recognition of optical flow activity confirmed the limitations for the use of inadequate feature extractions.

Chapter 8 – Results: Facial landmark analysis

8.1 Results

For the second image analysis of spontaneous emotion facial expression, rather than computing overall facial activity, the flow components were calculated at salient points of the face. Facial landmark analysis was carried out on frontal and profile facial images of 450 x 550 (width x height) and 250 x 550 (width x height) pixel dimensions, respectively. The 552 images set (1104 images) of baseline and emotional facial expressions of the whole face, profile left, and right sides of the face underwent pre-processing which involved image rotation and cropped using Photoshop Elements 13 (Adobe, USA).

Feature Extraction

Landmarks for each image were located manually to accurately identify specific facial points. The images were uploaded to MATLAB (R2017b, version 9.3, USA) and the landmarks were selected using the anthropometric landmarks in Farkas (1994) to locate a total of 32 soft tissue landmarks for the frontal and 18 soft tissue landmarks for profile facial images. Each landmark was assigned an arbitrary index number.

MATLAB (R2017b, version 9.3, USA) was used to perform the analysis of facial movement which occurred in between the neutral "baseline" image and an emotional response at the chosen landmark points. The purpose was to isolate flow at specific points by measuring the displacement of each facial landmarks from the neutral 'baseline' to peak of emotional expression. MATLAB (R2017b, version 9.3, USA) estimated the motion changes by calculating the Euclidean distance between the pair of sequential points of the two images using the x and y coordinates derived from each of the landmark points.

MATLAB (R2017b, version 9.3, USA) quantified information deduced from the changes across the baseline to an emotional response at specific landmark points for the frontal whole face, profile left and profile right sides of the face. The output results were produced in the form of a table that included the following information: x and y coordinates of the baseline (x1 and y1) and expression (x2 and y2) images; flow components u and v which represented the movement between the two x and two y coordinates, respectively. Where flow u was given by: x2 - x1 and flow v given by: y2 - y1. The resulting vector magnitude in pixels, and the direction of movement in degrees. Figure 8.1 shows an example of the analysis conducted by MATLAB for a subject. Where the vector displacement of the landmark points is calculated from the baseline to peak of emotional expression of fear from the profile left view. Table 8.1 shows the quantified information derived analysis of the individual expression (see Figure 2.9 and 2.10 for the corresponding position of the landmark on the human face).

Figure 8.1a and 8.1b: Landmark analysis for the expression of fear from the left profile facial view

(a) Baseline and peak of emotional expression

(b) Landmark displacement

Figure 8.1 displays the set of images where the displacement of 18 facial points was calculated from (a) the baseline to peak of emotional expression of fear from the profile left side. The calculated feature vectors are superimposed on (b) the baseline image to demonstrate the vector movements resulting from the change in expression. Permission granted for use of this image.

Table 8.1: Vector flow data for the left profile side registering fear

Baseline and Fear - Profile Left								
Landmark	x1	y1	x2	y2	flow u	flow v	Magnitude (Pixels)	Angle (˚)
Trichion	68	427	72	116	4	8	8.94	63.43
Glabella	53	339	48	211	-5	1	5.10	168.69
Sellion	63	302	59	249	-4	0	4.00	180.00
Medial Ear	62	330	63	227	1	-6	6.08	279.46
Apex Ear	93	344	88	212	-5	-5	7.07	225.00
Outer Ear	127	324	121	218	-6	9	10.82	123.69
Eye Superior	101	305	101	248	0	-2	2.00	270.00
Eye Inferior	99	284	102	263	3	4	5.00	53.13
Exocanthion	128	294	128	254	0	3	3.00	90.00
Pronasale	26	230	28	322	2	-1	2.24	333.43
Subnasale	66	203	65	343	-1	5	5.10	101.31
Alare	89	217	95	329	6	5	7.81	39.81
Labiale Sup	73	181	70	368	-3	2	3.61	146.31
Labiale Inf	85	153	94	426	9	-28	29.41	287.82
Chelion	110	163	118	402	8	-14	16.12	299.74
Supramentale	93	131	105	441	12	-21	24.19	299.74
Pogonion	87	104	102	469	15	-22	26.63	304.29
Gnathion	106	77	119	493	13	-19	23.02	304.38

Table 8.1 shows an example of the data output from displacement of 18 facial landmarks points from baseline to peak emotional expression. The following information as given for each landmark point: x and y coordinates from baseline and peak emotional expression, the resulting movement u and v, vector magnitude (pixels), and vector angle (degrees).

The parameter of investigation acquired the average magnitude and degree of movement which occurred in facial expressions between the baseline and peak emotional expression images. This was to observe any differences in the degree of facial movement between emotional responses. The vector magnitude values (pixel) and corresponding angles (˚) of directional movement for all landmarks were retrieved from each individual analysis and tabulated according to facial orientation for each emotional expression category. The mean vector magnitude and vector angles for the expression of amusement, sadness and fear for the frontal, left and right profile sides is summarised in Tables 8.2a, b and c.

Table 8.2a, 8.2b and 8.2c: Landmark mean vector magnitudes and angles of displacement for the frontal, left and right profile facial views

Table 8.2a Frontal

	Magnitude (SD) (Pixels)			Degrees (˚)		
Landmark	Amuse	Sadness	Fear	Amuse	Sadness	Fear
Trichion	5.68 (3.63)	5.07 (2.95)	7.27 (6.28)	199.74	66.21	293.54
Glabella	5.03 (3.17)	5.20 (3.28)	6.30 (4.58)	241.14	112.44	125.47
Sellion	5.63 (2.89)	5.04 (3.37)	5.50 (4.12)	219.63	29.08	5.71
Outer Ear R	5.23 (3.11)	4.88 (2.98)	7.17 (5.66)	92.80	89.87	42.64
Apex Ear R	6.23 (3.49)	6.49 (4.30)	10.04 (7.73)	237.17	337.27	101.12
Medial Ear R	6.25 (3.53)	6.59 (4.33)	7.62 (5.67)	166.49	74.36	44.91
Medial Ear L	6.35 (3.58)	7.07 (4.87)	9.12 (6.33)	203.22	169.37	83.61
Apex Ear L	5.83 (3.71)	5.56 (3.77)	8.31 (5.29)	292.71	91.59	273.13
Outer Ear L	5.65 (3.91)	5.21 (2.73)	6.80 (5.29)	283.42	83.80	144.06
Right Exo	5.87 (7.72)	3.37 (1.83)	5.83 (4.39)	189.01	16.56	150.90
Right Eye Sup	5.32 (3.89)	4.50 (2.93)	6.83 (5.84)	241.63	11.83	99.78
Right Endo	4.56 (6.83)	3.08 (1.67)	4.57 (4.47)	298.40	92.51	118.14
Right Eye Inf	4.62 (2.69)	3.39 (1.85)	4.50 (4.61)	124.43	18.27	335.42
Left Endo	3.79 (2.43)	3.13 (1.62)	4.30 (3.23)	129.83	229.69	293.98
Left Eye Sup	4.89 (3.50)	5.13 (3.70)	5.87 (4.83)	287.26	22.29	95.31
Left Exo	5.38 (3.30)	4.86 (2.40)	5.44 (3.09)	338.04	49.96	95.86
Left Eye Inf	4.51 (2.82)	3.93 (2.06)	4.64 (3.02)	84.24	87.39	22.11
Pronasale	4.83 (2.63)	3.31 (1.77)	5.34 (3.89)	180.42	62.51	59.66
Alare R	7.47 (4.18)	3.15 (1.57)	4.71 (4.37)	123.94	61.28	92.24
Alare L	7.05 (3.95)	3.42 (1.68)	5.10 (4.30)	56.25	74.70	75.91
Labiale S	8.54 (4.30)	3.61 (2.63)	5.64 (5.42)	88.89	101.71	33.79
Labiale Inf	8.06 (4.81)	6.64 (4.15)	10.54 (10.58)	91.02	96.57	212.03
R Crista Ph	8.38 (4.33)	4.37 (2.27)	6.26 (5.16)	100.63	93.78	143.77
L Crista Ph	8.41 (4.56)	4.34 (2.70)	6.03 (4.34)	79.59	70.59	209.16
Chelion R	17.97 (12.64)	6.81 (5.99)	9.68 (7.58)	118.82	48.56	229.02
Chelion L	18.90 (12.57)	7.59 (5.64)	9.57 (7.07)	55.01	77.21	61.23
Pogonion	6.58 (3.29)	6.73 (4.83)	10.69 (9.82)	100.36	107.37	78.87
Gnathion	6.31 (3.52)	5.70 (3.65)	10.02 (9.06)	288.48	167.36	29.11
Zygion R	7.53 (5.49)	5.60 (4.56)	7.91 (5.08)	96.79	28.46	344.30
Zygion L	8.30 (5.87)	6.76 (5.95)	7.72 (4.54)	69.07	78.48	53.85
Gonion R	10.97 (6.50)	6.33 (3.29)	10.02 (7.19)	128.17	332.42	266.67
Gonion L	11.88 (7.53)	6.00 (4.22)	10.21 (7.77)	51.92	31.03	99.77

Table 8.2a displays a summary for mean vector magnitude, standard deviation, and corresponding absolute degree of directional movement (˚) for 32 landmarks from frontal facial view for the emotional expression of amusement, sadness and fear.

Key: SD = Standard Deviation; R = Right; L = Left; Sup = Superius; Inf = Inferius; Exo = Exocanthion; Endo = Endocanthion; Ph = Philtri

Table 8.2b Left profile

	Magnitude (SD) (Pixels)			Degrees (˚)		
Landmark	Amuse	Sadness	Fear	Amuse	Sadness	Fear
Trichion	6.10 (4.05)	3.94 (2.46)	7.84 (5.37)	38.38	193.66	323.93
Glabella	4.61 (2.97)	4.26 (3.20)	7.25 (4.97)	180.58	148.58	30.31
Sellion	4.93 (2.37)	3.57 (2.04)	4.77 (3.63)	181.67	161.45	182.37
Medial Ear	5.54 (3.37)	4.76 (2.82)	8.45 (6.24)	214.38	187.78	18.54
Apex Ear	6.39 (3.62)	5.02 (2.66)	8.55 (6.12)	242.56	189.02	5.66
Outer Ear	8.11 (4.76)	5.83 (3.94)	8.11 (5.56)	215.76	140.84	131.56
Eye Superior	5.8 (2.79)	3.62 (2.16)	6.74 (6.00)	210.77	106.82	56.00
Eye Inferior	5.91 (3.75)	3.61 (1.79)	5.23 (3.39)	160.36	165.57	336.72
Exocanthion	6.04 (3.37)	4.19 (2.37)	6.15 (4.38)	200.71	187.54	177.95
Pronasale	3.64 (2.29)	2.38 (1.50)	3.23 (1.91)	255.23	107.05	47.31
Subnasale	4.72 (3.19)	2.75 (1.71)	3.70 (2.22)	34.48	120.56	99.83
Alare	5.63 (3.58)	3.59 (1.87)	4.35 (3.08)	127.07	163.59	95.62
Labiale Sup	7.39 (4.42)	4.55 (2.64)	5.08 (3.60)	46.88	73.63	87.56
Labiale Inf	8.34 (5.06)	6.51 (4.22)	13.24 (12.54)	49.47	247.24	198.76
Chelion	14.46 (6.69)	5.08 (3.24)	12.66 (11.97)	48.20	26.40	70.95
Supramentale	7.10 (4.53)	6.61 (4.25)	12.5 (11.33)	329.34	169.92	83.33
Pogonion	7.31 (5.55)	8.66 (6.54)	14.25 (11.8)	282.32	90.18	204.31
Gnathion	7.29 (4.86)	7.65 (5.90)	13.91 (11.25)	255.08	100.40	102.12

Table 8.2c Right profile

	Magnitude (SD) (Pixels)			Degrees (˚)		
Landmark	Amuse	Sadness	Fear	Amuse	Sadness	Fear
Trichion	5.71 (3.81)	3.76 (1.92)	6.80 (4.16)	105.24	97.24	289.01
Glabella	4.95 (3.13)	4.17 (2.46)	6.68 (5.48)	354.01	81.74	96.38
Sellion	4.60 (2.54)	3.77 (2.08)	4.61 (3.24)	20.27	51.83	111.45
Medial Ear	4.68 (2.82)	4.51 (2.82)	6.53 (4.70)	331.73	95.76	102.08
Apex Ear	6.15 (3.92)	5.42 (3.73)	9.44 (7.48)	338.45	137.07	21.49
Outer Ear	7.53 (4.59)	7.16 (5.35)	8.65 (7.78)	344.45	29.78	348.43
Eye Superior	4.66 (2.80)	3.87 (1.94)	6.94 (5.41)	323.90	356.37	60.52
Eye Inferior	4.73 (2.65)	3.80 (2.26)	4.79 (3.29)	33.45	89.12	93.37
Exocanthion	5.53 (3.24)	4.36 (3.44)	5.51 (4.02)	8.00	9.32	135.21
Pronasale	3.19 (1.92)	2.02 (1.26)	2.28 (1.45)	255.70	49.39	160.10
Subnasale	4.66 (2.98)	2.75 (1.77)	3.06 (2.02)	122.48	59.04	100.30
Alare	6.27 (3.46)	3.11 (1.70)	4.29 (3.04)	70.51	53.35	104.36
Labiale Sup	7.79 (4.15)	4.36 (2.90)	3.86 (2.48)	125.76	35.91	77.29
Labiale Inf	8.65 (7.58)	6.71 (4.51)	12.14 (13.06)	120.74	35.31	200.92
Chelion	16.81 (7.08)	6.14 (4.38)	10.59 (8.10)	131.89	263.72	31.74
Supramentale	6.74 (4.58)	6.36 (4.58)	11.19 (11.56)	143.42	354.29	143.32
Pogonion	8.89 (5.15)	8.11 (6.96)	12.22 (11.85)	317.02	359.07	337.64
Gnathion	7.32 (4.91)	7.21 (5.03)	11.99 (11.85)	4.82	86.78	19.01

Tables 8.2b and c displays a summary for mean vector magnitude, standard deviation, and corresponding absolute degree of directional movement (˚) for 18 landmarks from 8.2b the left and 8.2c the right profile sides for the emotional expression of amusement, sadness and fear.
Key: SD = Standard Deviation; Sup = Superius; Inf = Inferius

Emotion Maps

Information pertaining to mean vector magnitudes and mean vector angles were used to develop emotion maps to visually compare the movement between the three expressions at the landmark point. Similar to the optical flow emotion map, however compass is divided into 36 sectors of 10˚ angles with 0˚ starting East rotating counterclockwise. They display the average displacement of a landmark point with respect to the origin for each emotion’s directional movement falling into one of the 36 directional bins.

It is important to note that this emotion map is a visual illustration of the vectors derived from landmark analysis to summarise the various displays of emotion activity. Furthermore, the emotion maps are not representations of the face where different sectors correlate to different sections of the face.

Frontal

Emotion map for the landmarks for frontal facial orientation are illustrated in Figure 8.2, where the activity of amusement is denoted in yellow, sadness blue and fear red. The colour bins represent the mean vector displacement. With respect to the orientation of the face, movement generated between 90˚ to 270˚ represents movements directed towards the right of the subjects’ face and 0˚ to 90˚ and 270˚ to 360˚ represents facial movements directed to the left side of the subjects’ face.

The landmark areas can be grouped by facial sections:

- Forehead and furrows: Trichion, Glabella and Sellion, which are designated Landmarks 1-3.
- Eyebrow area: Outer, apex and inner eyebrow (Landmarks 4-9)
- Orbital area: Exocanthion, Palpebral Superior, Endocanthion and Palpebral Inferius (Landmarks 10-17)
- Nasal area: Pronasale, right and left Alare (Landmarks 18-20)
- Oral area: Labiale superior and inferior, Crista Philtri, Chelion (Landmarks 21-26)
- Lower non- feature area: Pogonion, Gnathion, Zygion and Gonion (Landmarks 27-32).

Figure 8.2: Emotions maps for mean vector magnitudes (pixels) for the frontal facial views

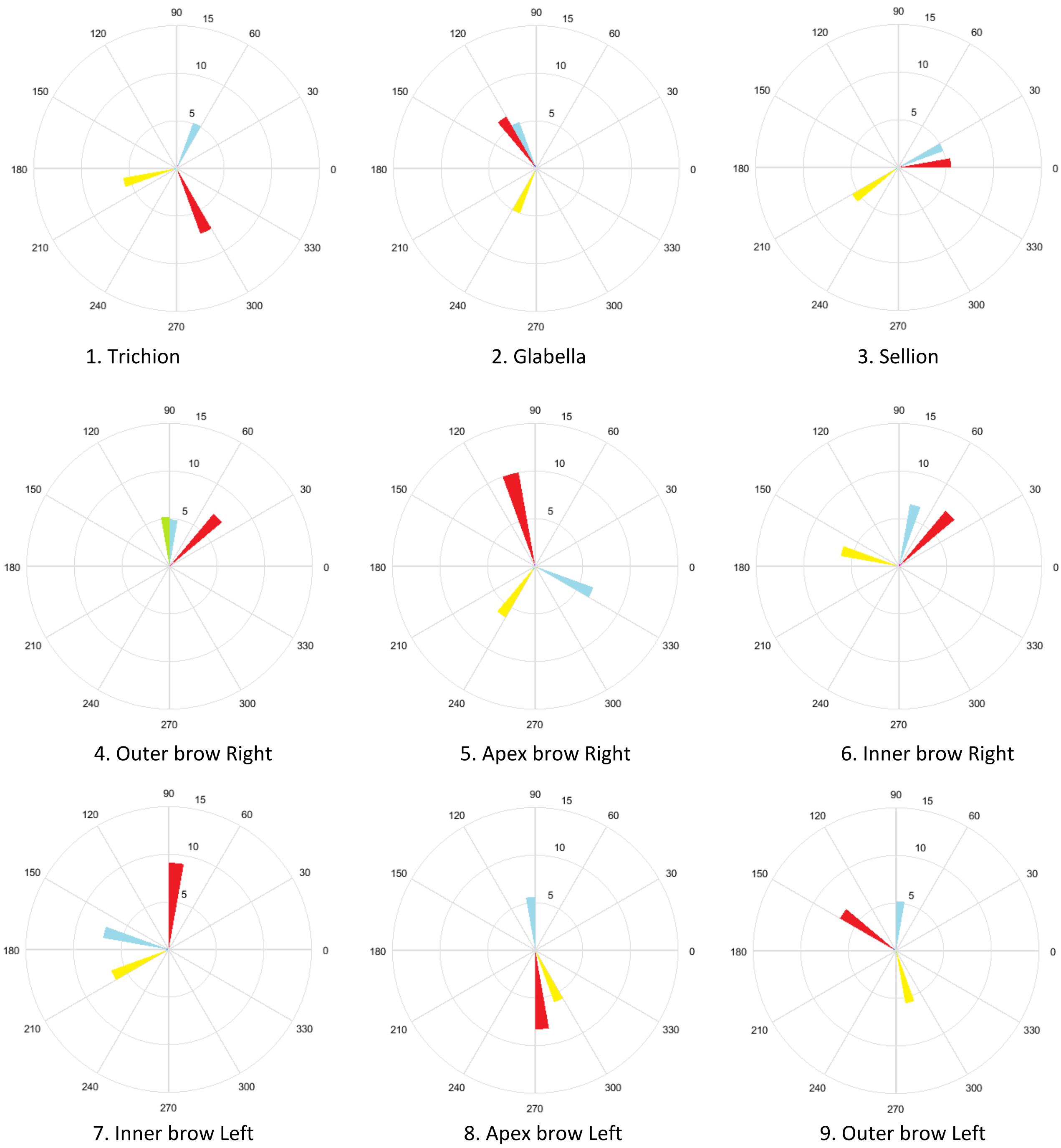


Figure 8.2 display emotion maps of average vector magnitudes for the expression of amusement, sadness and fear at specific landmark points of the face from the frontal facial orientations. Each emotion category is colour coded where yellow is designated amusement, blue for sadness, and red for fear. The Landmarks have assigned indices.

Amusement Sadness Fear

Figure 8.2: Vector magnitudes – frontal landmarks continued.

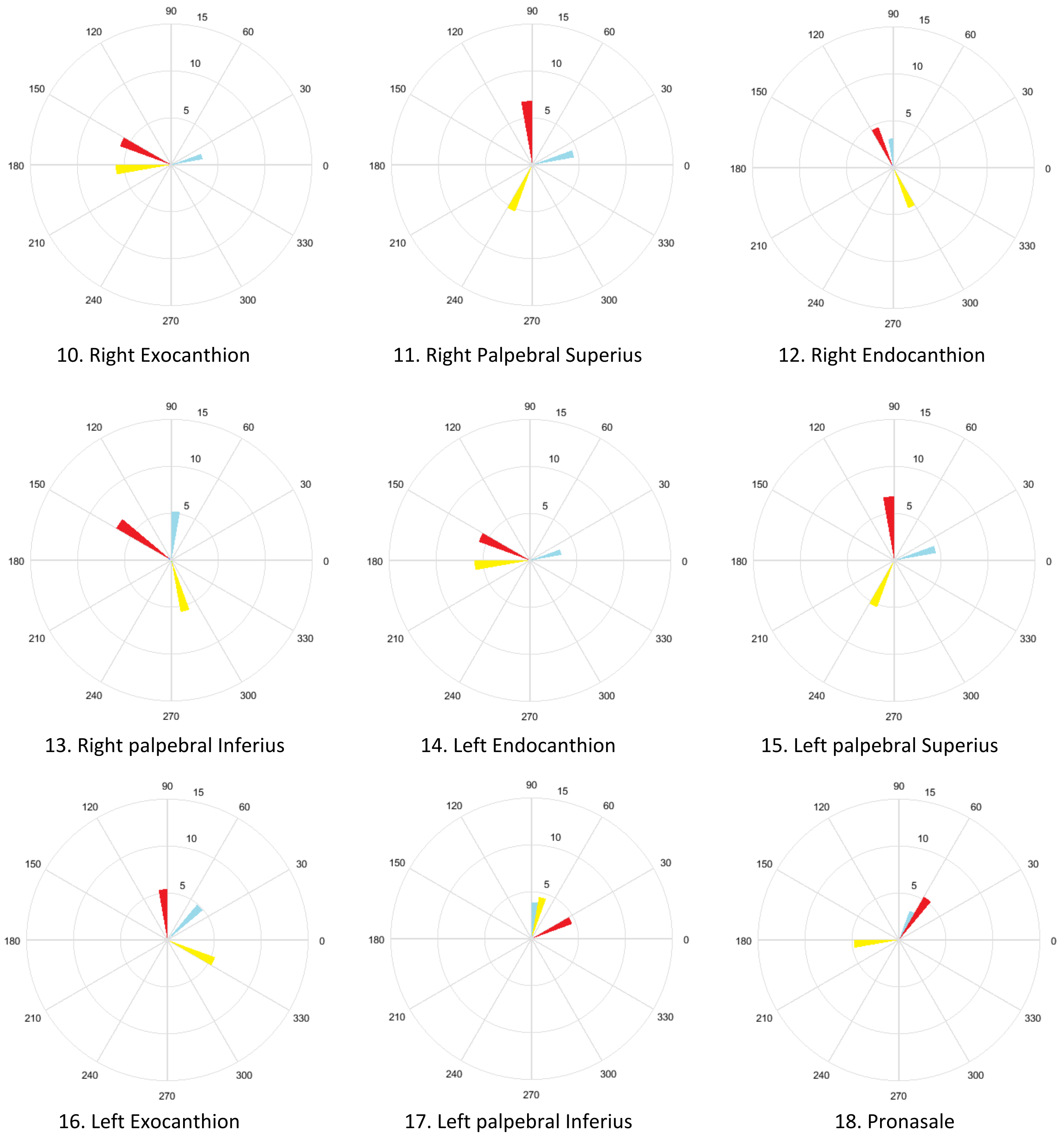
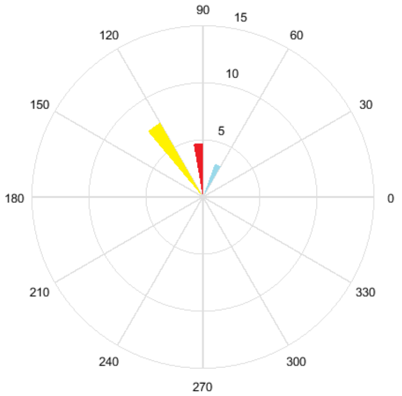


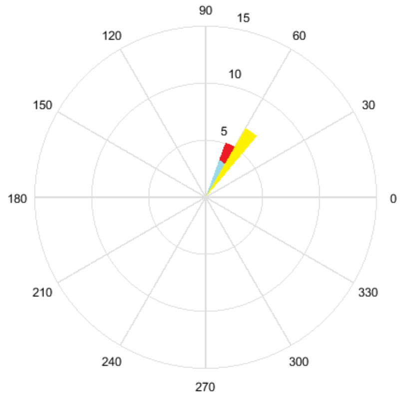
Figure 8.2 display emotion maps of average vector magnitudes for the expression of amusement, sadness and fear at specific landmark points of the face from the frontal facial orientations. Each emotion category is colour coded where yellow is designated amusement, blue for sadness, and red for fear. The Landmarks have assigned indices.

Amusement Sadness Fear

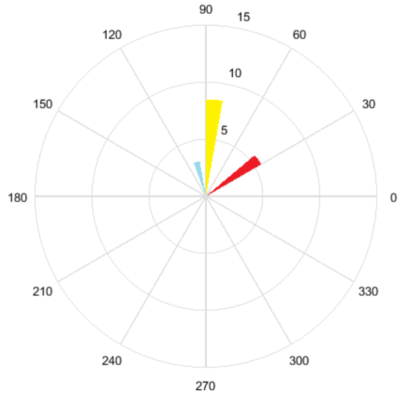
Figure 8.2: Vector magnitudes – frontal landmarks continued.



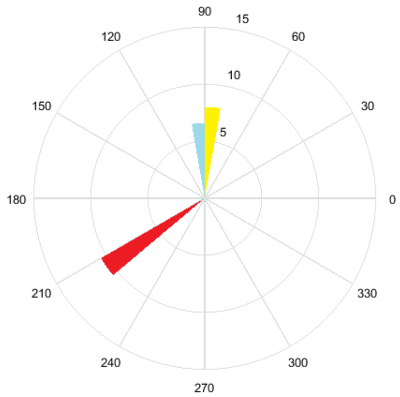
19. Right Alare



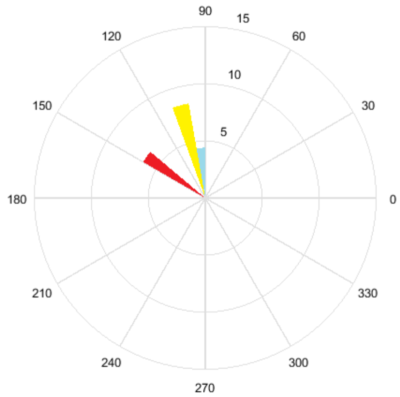
20. Left Alare



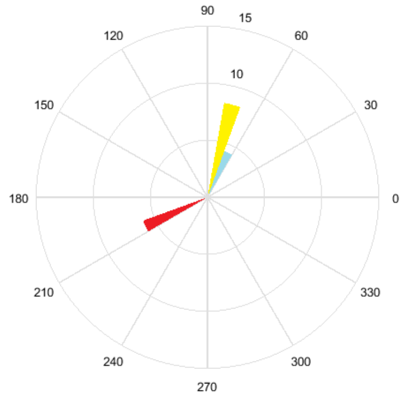
21. Labiale Superius



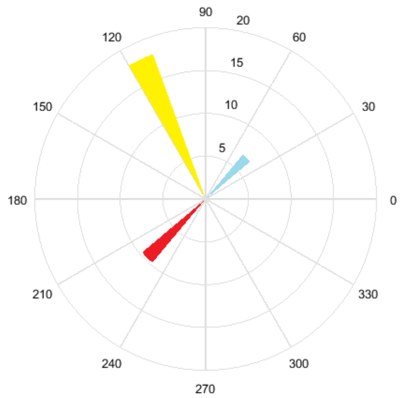
22. Labiale Inferius



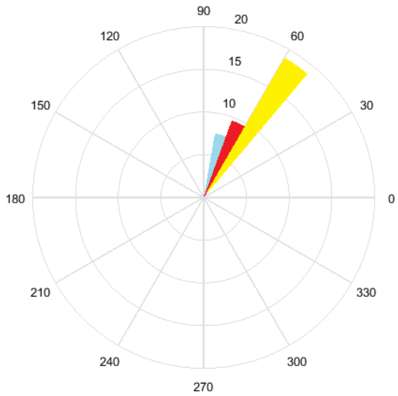
23. Right Crista Philtri



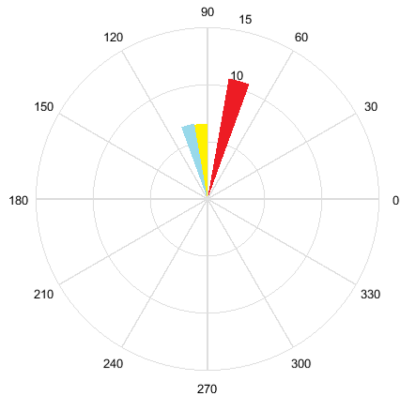
24. Left Crista Philtri



25. Right Chelion



26. Left Chelion

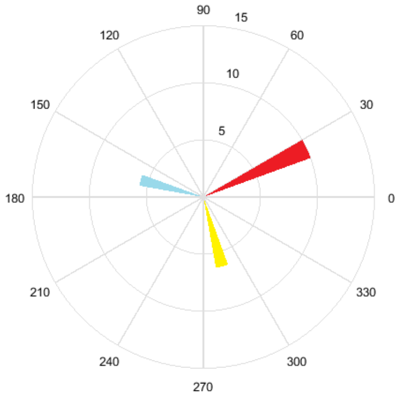


27. Pogonion

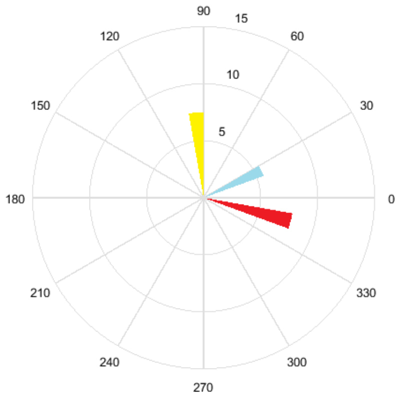
Figure 8.2 display emotion maps of average vector magnitudes for the expression of amusement, sadness and fear at specific landmarks of the face from the frontal facial orientations. Each emotion category is colour coded where yellow is designated amusement, blue for sadness, and red for fear. The Landmarks have assigned indices.

Amusement Sadness Fear

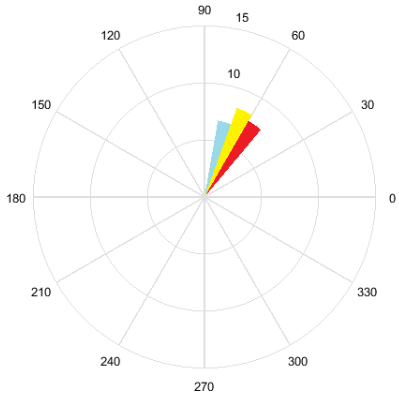
Figure 8.2: Vector magnitudes – frontal landmarks continued.



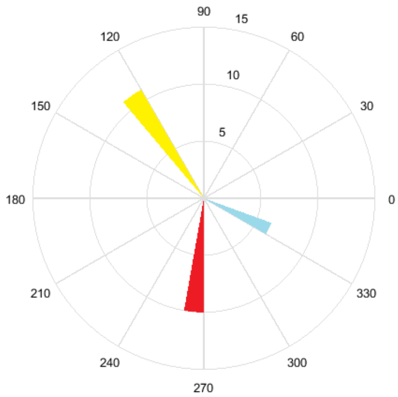
28. Gnathion



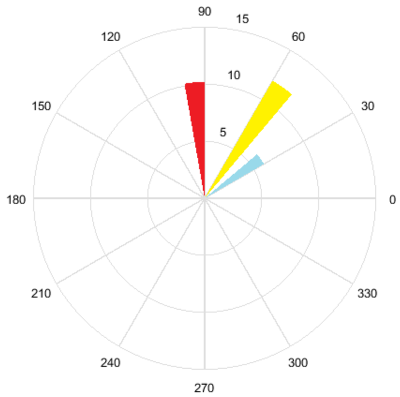
29. Right Zygion



30. Left Zygion



31. Right gonion



32. Left gonion

Figure 8.2 display emotion maps of average vector magnitudes for the expression of amusement, sadness and fear at specific landmark points of the face from the frontal facial orientations. Each emotion category is colour coded where yellow is designated amusement, blue for sadness, and red for fear. The Landmarks have assigned indices.

Amusement Sadness Fear

Movement activity in the forehead area for amusement was constrained between 190˚ to 250˚. General elevation of upwards movement for the expressions of fear and sadness with the exception of fear at the Trichion landmark to which activity was directed towards 290˚ to 300˚.

Greater magnitude movement for inner and apex of the eyebrows with elevated movements from fear and sadness reflecting inner raising of the brows. General vector movements around the right orbital region for amusement directed down, with Exocanthion oriented towards 180˚ and Endocanthion towards 290˚. Conversely, lowering of the left Palpebral superius and raising of left Palpebral inferius, movement activity for the left Exocanthion and Endocanthion were directed laterally towards 300˚ and 180˚, respectively. All movements correlate to decreasing eye aperture.

For the expressions of fear and sadness general elevation in movements of orbital landmarks could be observed from the emotion maps with sadness generating movements between 10˚ to 90˚ and 20˚ to 160˚ for fear. Similarly, general upwards and outwards movement for the nasal area indicating nostril dilation across the three expressions.

For the oral areas, greater magnitude movement was between 50˚ to 120˚ as observed for the expression of amusement, meaning activity was directed upwards and obliquely outwards. Likewise, elevated landmark movements for the expression of sadness but to a lesser extent than amusement with movements directed between 40˚ to 100˚. Fear appeared somewhat indiscriminate, and showed elevation of the Labiale superius, right Crista philtri and left Chelion landmarks whereas at the Labiale inferius, left Crista philtri and right Chelion, activity was constrained between 200˚ to 230˚.

Overall, sadness generated the least amount of movement overall with greater movement generated for the expressions of fear and amusement, on particularly the eyebrow region for fear and oral regions for amusement.

Profile Left

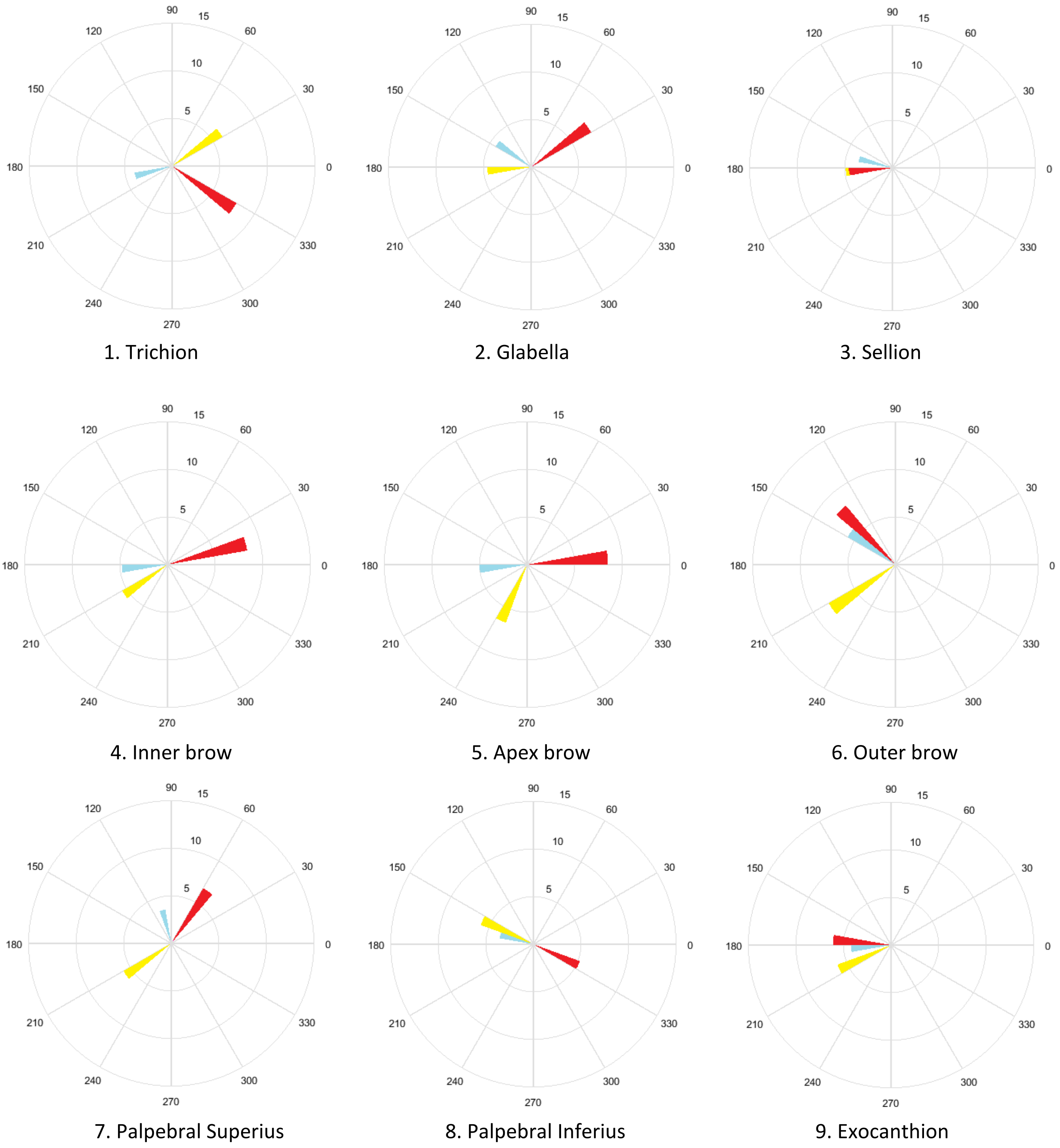
Similar to the analysis of the frontal view, emotion maps displayed in Figure 8.3 depicts the average magnitudes and their directional movement. This was done for the facial expressions of amusement, sadness, and fear for the left profile of the face. Where the activity of amusement is denoted in yellow, sadness blue and fear red. With respect to the orientation of the face, feature vector movement generated between 90˚ to 270˚ represents movements anteriorly or medial and 0˚ to 90˚ and 270˚ to 360˚ represents movements directed laterally or posteriorly.

Greater magnitude of movement was observed in the face for fearful expressions, and in the lower face area for amusement. Movement activity of landmarks representing amusement expression for the eyebrows and orbital areas were constrained between 150˚ to 220˚. Observations of movement generated between 30˚ to 60˚ of oral landmarks: Labiale (superius and inferius), Chelion (Landmarks 13 - 15). Landmarks representing the Pogonion, Gnathion, Supramentale (Landmarks 16-18) constrained between 250˚- 300˚ reflects downward orientation of movement activity.

Greater movement for the expression of sadness was observed in the activity of landmarks in lower portions of the face which were directed upwards with the exception of the Labial inferius directed downwards between 240˚ to 250˚. The eyebrows and orbital landmarks activities were restricted between 140˚ to 190˚.

For fear, movement activity for inner and apex of the eyebrows was oriented towards 0˚ to 20˚. General activity directed upwards for landmarks of the lower half of the face was constrained between the directions of 40˚ to 110˚. With the exception of the Labiale inferius and Pogonion with movement concentrated towards 190˚ to 210˚. Greater activity for amusement and fear was observed at the Labiale inferius and Chelion. With fear directed obliquely upwards but for the inferior area and pogonia, where depression was observed which may be due to the mouth being open.

Figure 8.3: Emotions maps for mean vector magnitudes (pixels) for the left profile facial views

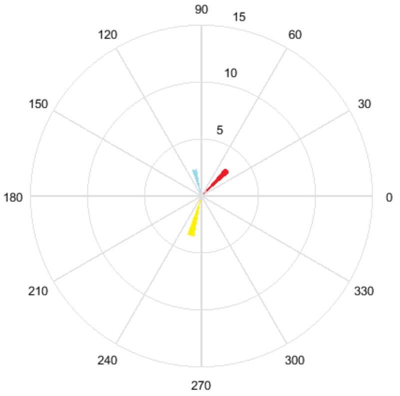


1. Trichion 2. Glabella 3. Sellion
4. Inner brow 5. Apex brow 6. Outer brow
7. Palpebral Superius 8. Palpebral Inferius 9. Exocanthion

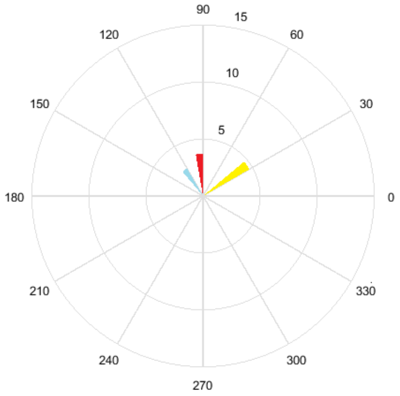
Figure 8.3 displays the emotions maps for mean magnitudes (pixels) of facial activity for the left profile facial orientation. Each emotion maps shows the average vector magnitude for the expressions of amusement, sadness and fear at specific facial landmarks. Each emotion category is colour coded.

Amusement Sadness Fear

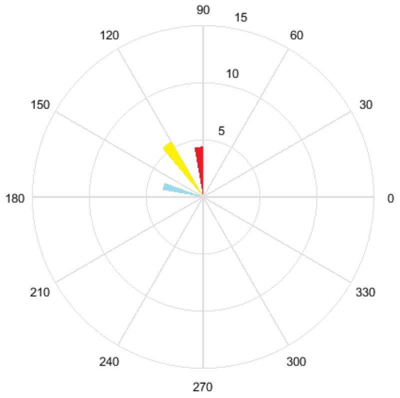
Figure 8.3: Vector magnitudes – profile left landmarks continued.



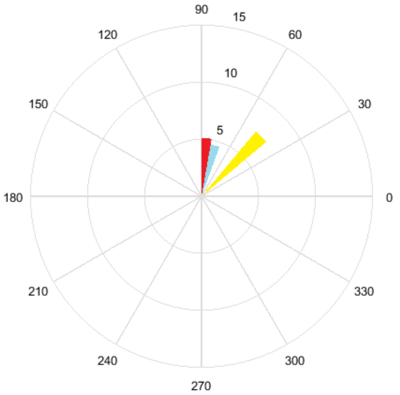
10. Pronasale



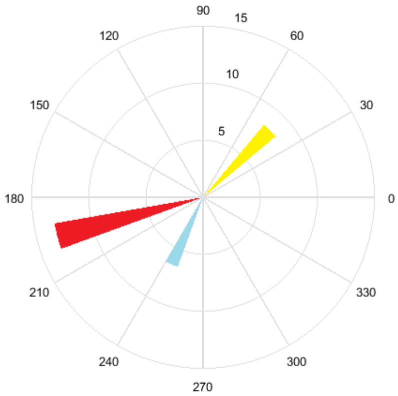
11. Subnasale



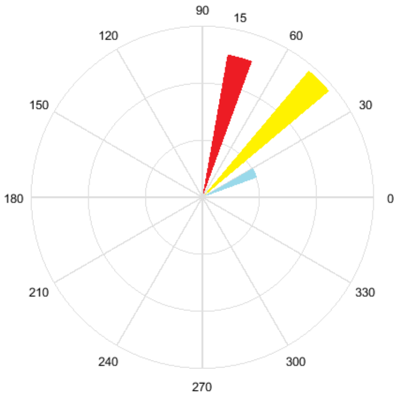
12. Alare



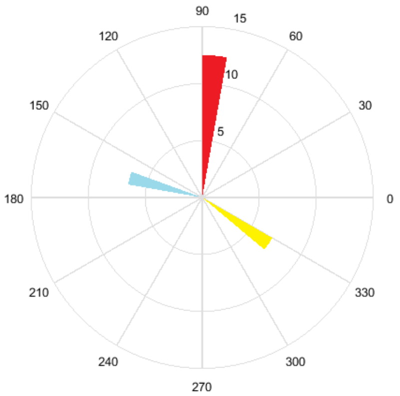
13. Labiale Superius



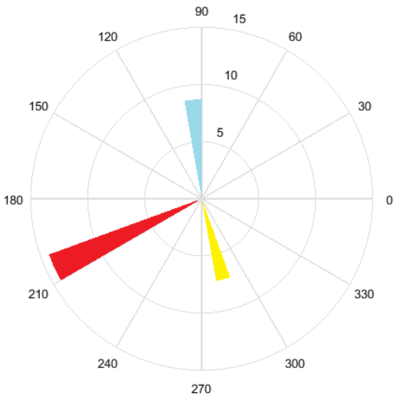
14. Labiale Inferius



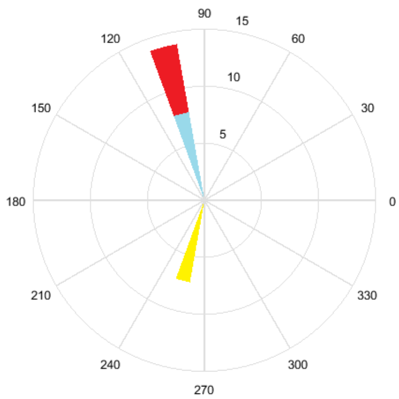
15. Chelion



16. Supramentale



17. Pogonion



18. Gnathion

Figure 8.3 displays the emotions maps for mean magnitudes (pixels) of facial activity for the left profile facial orientation. Each emotion maps shows the average vector magnitude for the expressions of amusement, sadness and fear at specific facial landmarks. Each emotion category is colour coded.

Amusement Sadness Fear

Profile Right

The emotion maps displayed in Figure 8.4 depict the average magnitude and their directional movement. This is for the facial expressions of amusement, sadness, and fear for the right profile of the face. Where the activity of amusement is denoted in yellow, sadness blue and fear in red. With respect to the orientation of the face, movement generated between 0˚ to 90˚ and 270˚ to 360˚ represents movements anteriorly or medially, and 90˚ to 270˚ represents movements directed laterally or posteriorly.

Vector movements for the eyebrow areas for the expression of amusement were constrained between 330˚ to 350˚. Additionally, the lowering of Palpebral superius and raising of Palpebral inferius with movements observed to be oriented towards 320˚ to 330˚ and 30˚ to 40˚, respectively. General elevation in vector movements for sadness between 20˚ to 140˚ for eyebrow regions and Palpebral inferius. Movement of Exocanthion and Palpebral superius directed towards 0˚ to 10˚ and 350˚ to 360˚. Observations of emotion maps for fearful expressions reveals general elevation of landmarks in the eyebrow and orbital areas with movements generated between 20˚ to 110˚ with the exception of lowering of the outer brow oriented between 340˚ to 350˚.

For all three expressions, the movement of the Subnasale and Alare in the directions between 50˚ to 130˚ was noted. However, differences were seen in directional movements of the Pronasale with vectors directed between 250˚ to 260˚, 40˚ to 50˚, and 160˚ to 170˚ for amusement, sadness, and fear, respectively.

Concerning landmarks in the oral areas: Labiale superior and inferior, Chelion, elevated movement was seen for expression of amusement directed obliquely upwards with movement concentrated between 120˚ to 140˚. Greater magnitude movement was observed at the Labial inferius for fear to the direction 200˚ to 210˚ and general elevation of upper lip movement due to activity of Chelion and Labiale superius in the direction between 30˚ to 80˚. Whereas for the expression of sadness, vertical movement of Chelion directed downwards and oblique movement of the Labiale superius and inferius at 30˚ to 40˚ was observed.

Greater activity movement could be observed in the chin area: pogonion, gnathion, (Landmarks 16-18). Similar directional movements for amusement and fear could be seen whereas pattern differences emerge for sadness for example with movement activity of the Supramentale oriented towards 350˚ to 360˚, compared to 140˚ to 150˚ for amusement and fear. Greater fear movement was at the Pogonion, Gnathion, and Supramentale directed anteriorly. Greater activity for amusement and fear was seen at the oral area of Labiale inferius and Chelion.

Figure 8.4: Emotions maps for mean vector magnitudes (pixels) for the right profile facial views

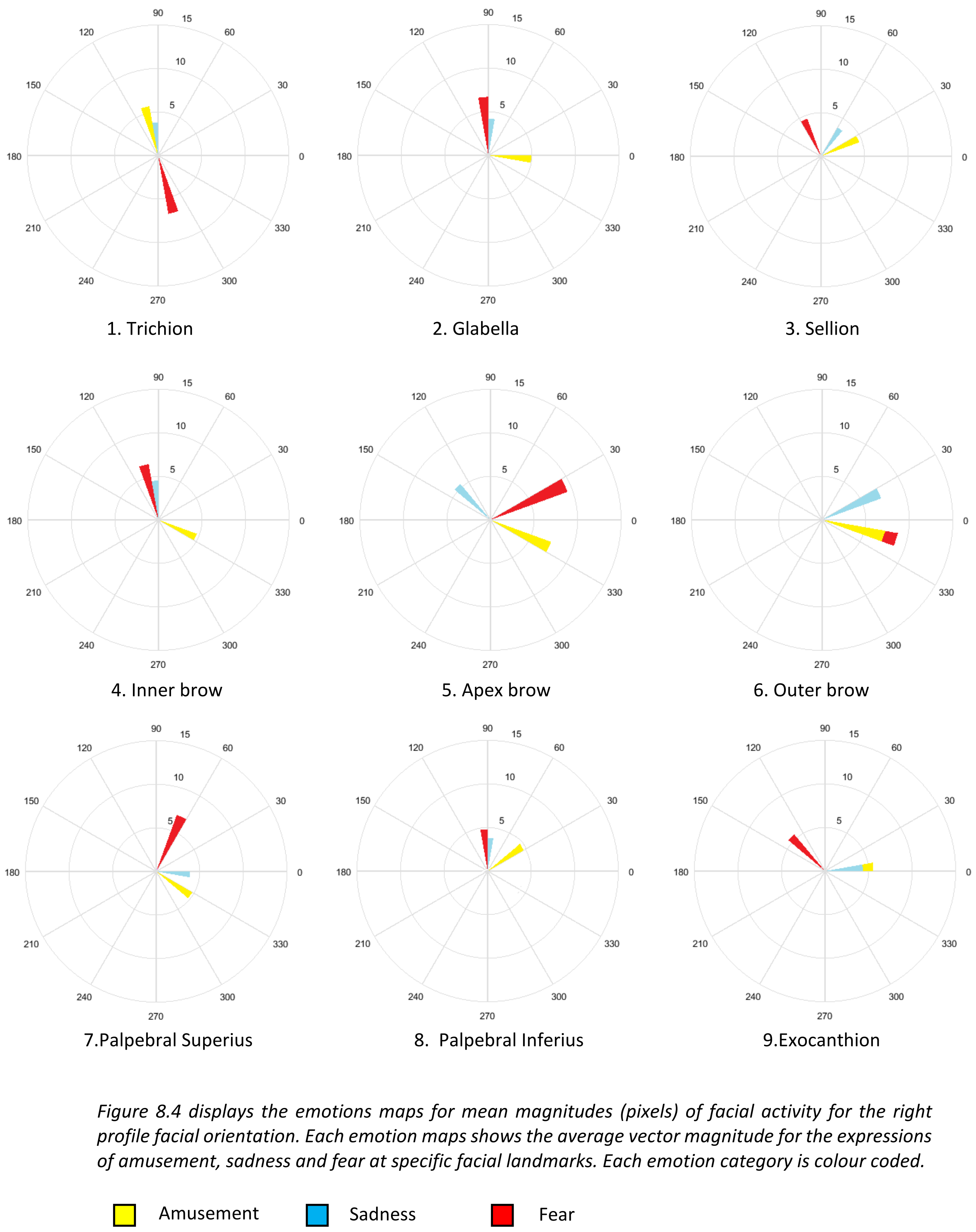
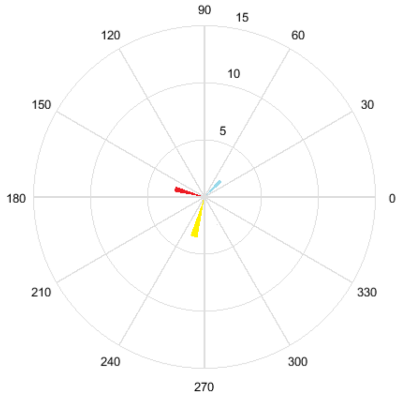
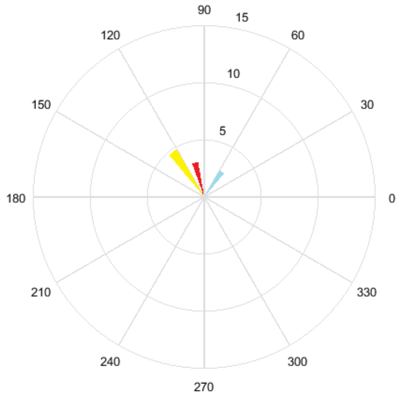


Figure 8.4 displays the emotions maps for mean magnitudes (pixels) of facial activity for the right profile facial orientation. Each emotion maps shows the average vector magnitude for the expressions of amusement, sadness and fear at specific facial landmarks. Each emotion category is colour coded.

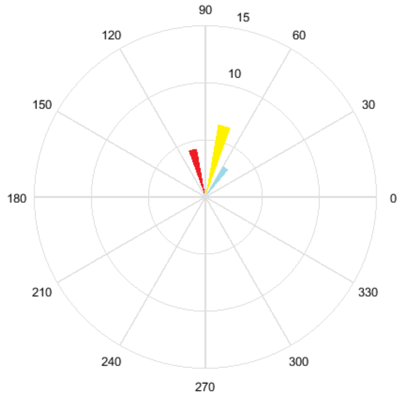
Figure 8.4: Vector magnitudes– right profile landmarks continued.



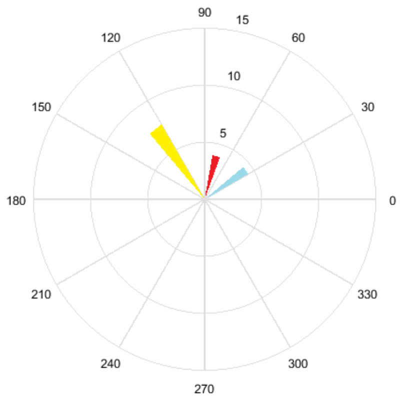
10. Pronasale



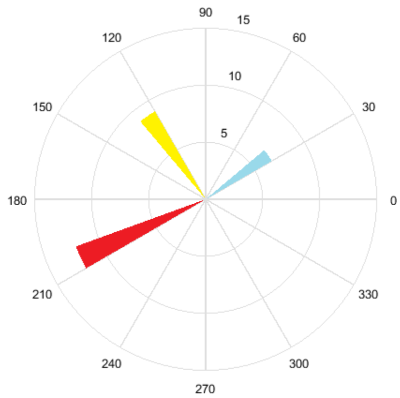
11. Subnasale



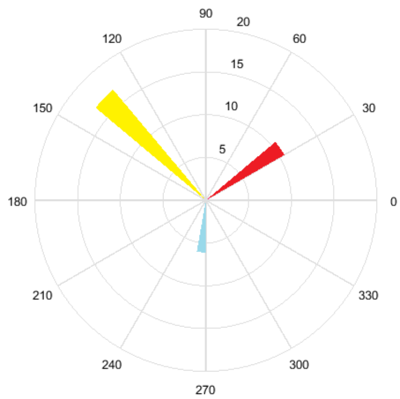
12. Alare



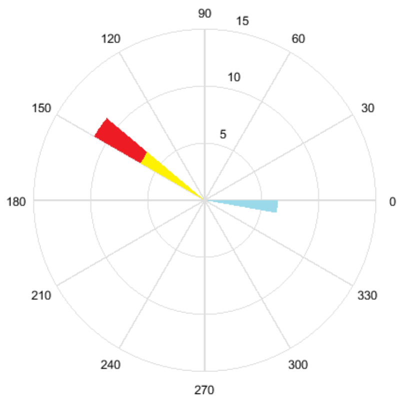
13. Labiale Superius



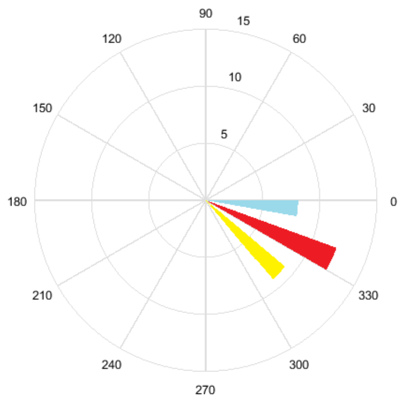
14. Labiale Inferius



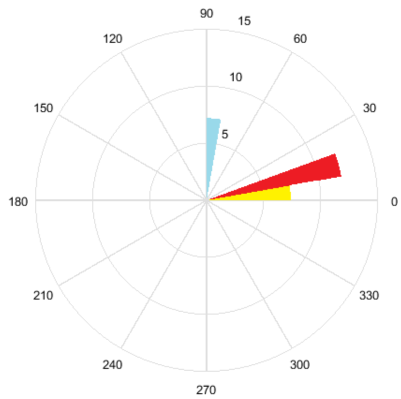
15. Chelion



16. Supramentale



17. Pogonion



18. Gnathion

Figure 8.4 displays the emotions maps for mean magnitudes (pixels) of facial activity for the right profile facial orientation. Each emotion maps shows the average vector magnitude for the expressions of amusement, sadness and fear at specific facial landmarks. Each emotion category is colour coded.

Amusement Sadness Fear

Classification

This study utilised various classifiers to observe whether three different emotional facial expressions classes could be differentiated, using the feature vectors ascertained from tracking the landmark output as the predictor variable. Classification analyses were undertaken using the Classification App in MATLAB version 2017A. Predictive accuracy scores were provided as a measure of the performance of the classifiers using 36 predictors with 3 response classes with a 5-fold cross-validation for the frontal and 18 predictors with 3 response classes with a 5-fold cross-validation for the profile sides. This was calculated for two sets of feature variables, one set representing the mean magnitude values and the other set of pertaining to movement direction of vectors.

Magnitude of Movement

The average vector magnitude and direction movement for facial expressions of sadness, amusement and fear was analysed across the three facial views. Table 8.3 shows the predictive accuracy recognition of the model in percentage for each facial orientation for classifiers that achieved the top four accuracy recognition (%) for vector magnitude. The SVM achieved the highest accuracy **r**ecognition of 72.3% for the left profile of the face and LDA achieving 69.6% recognition accuracy for right profile sides. Similarly, the RUSBoosted tree ensemble classifier achieved an accuracy of 71.2% for the frontal facial orientation, followed by the Simple Tree classifier (frontal = 61.4%; left profile = 66.3%) and the LDA achieving the lowest accuracy score of 62.5%.

Table 8.3: Overall recognition accuracy of classifiers for emotional facial expressions

Landmark Magnitude		SVM (%)	SIMPLE TREE (%)	LDA (%)	RUSBoosted Tree ensemble (%)
	Front	63	66.8	62.5	**71.2**
	Left	**72.3**	64.7	69	69.6
	Right	66.8	64.1	**69.6**	67.9

Table 8.3 shows the performance comparisons of the top four classifiers using landmark facial data for magnitude. The models using accuracy (%) as a metric for evaluating the true class.

Key: SVM = Support Vector Machine; LDA = Linear Discriminant Analysis; KNN = K- Nearest Neighbors

Confusion matrices for the highest performing model for the frontal, profile left, and right sides are shown in Tables 8.4a, b and c where each column represents a predicted class and row represents the true classes with which the expression belongs. Correct predictions run along the principal diagonal.

Confusion matrix of the RUSBoosted tree ensemble classifier for the frontal facial orientation yielded high detection of amusement expressions at which 83/96 (86%) are correctly classified, and also accounted for 86% of the total number of expressions (97) that the classifier predicted as being amusement. For classification of sadness, 26/44 (59%) expressions of sadness were detected, furthermore accounted for 53% of the 49 predictions. When 44 expressions of fear were presented, 50% of those were detected and accounted for 58% of the 38 instances for which fear class was predicted.

Similarly, for the profile sides, the breakdown classification performance of the SVM classifier for the left profile side shows that 85 out of 96 (89%) amusement images were correctly classified and accounted for 81% of the 105 instances for which amusement class was predicted. Compared with sadness where 32 out of possible 44 expressions of sadness (73%) were correctly classed and making up 60% of the 53 predictions for sadness. Fear was correctly classified for 16 of the 44 (36%) expressions and accounted for 62% of the 26 instances for which fear was predicted. However, equal numbers were misclassified as “sadness” and a further 12 classed as “amusement.”

Examination of the confusion matrix of the LDA classifier for the right profile side showed that when 96 amusement expression were presented, the LDA classified 79 (82%) expressions of amusement, classifying 12 (13%) expressions as sad and 5 (5%) expressions as fear. The 79 correct classified expressions of amusement also accounted for 80% of overall predicted amusement expressions. When 44 expressions of sadness and fear were presented, 28/44 (64%) and 21/44 (48%) cases were correctly classed and made up 51% and 70% of the 55 and 30 predictions for sadness and fear, respectively.

Table 8.4a, 8.4b and 8.4c: Confusion matrices for the best performing classifiers for the frontal, left and right profile facial views

Table 8.4a Confusion matrix for frontal view using the Boosted Tree classifier

		Predicted Image Classes		
	Class	Amuse	Sad	Fear
True Classes	Amuse	83	6	7
	Sad	9	26	9
	Fear	5	17	22

Table 8.4c Confusion matrix for profile left side using the SVM classifier

		Predicted Image Classes		
	Class	Amuse	Sad	Fear
True Classes	Amuse	85	5	6
	Sad	8	32	4
	Fear	12	16	16

Table 8.4c Confusion matrix for profile right side using the LDA classifier

		Predicted Image Classes		
	Class	Amuse	Sad	Fear
True Classes	Amuse	79	12	5
	Sad	12	28	4
	Fear	8	15	21

Tables 8.4a, b and c display confusion matrices which illustrates the breakdown in recognition of images of three emotional facial expressions: amusement, sadness and fear. Each confusion matrix represents the top performing classifier for each facial orientation. The number of expressions that were correctly classified runs along the principal diagonal cells highlighted green.

Key: Amuse = Amusement; SVM = Support Vector Machine; LDA = Linear Discriminant Analysis

Using the confusion matrix, additional information was derived such as true positives (TP), which depict the number samples that were correctly classified. False positives (FP), which is the number of emotional facial expression images who were incorrectly classified as expressing that emotion. False negatives (FN) which indicates the expression for a particular emotion class was classified by the model as not belonging to that class. And finally, true negatives (TN), which is when the expression not belonging to that emotion was correctly classified as being negative for that expression class.

The results were summarised in Tables 8.5a, b and c displaying the number of true negative, false positive, false negative, true negative for each expression class as well as the precision, recall and F_1 measure which were converted to percentages (%). This was done for the RUSBoosted tree ensemble classifier for the frontal facial orientation, Support Vector Machine (SVM) classifier for the Left Profile and LDA classifier for Right Profile side.

Higher precision and recall were observed for the expression of amusement across different facial views, ranging from 79% to 88.54% and resulting in obtaining a higher F_1 measure. This was due to the high detection of amusement and precision with which the expression was being predicted.

Sadness yielded higher recall scores compared to precision scores, which suggests that the number of predictions for sadness expressions exceeded the actual number of sadness expression that was correctly predicted, thus contributing to the decrease in overall F_1 measure. However, the best performing model for predicting sadness expression was the SVM classifier for the left profile side obtaining the highest precision (60.38%), accuracy (72.73%) and F_1 measure (69.58%).

Despite obtaining the lowest detection rate across all facial orientations compared to amusement and sadness, precision scores for classification of fear were higher than recall. Suggesting that for the model performed moderately well to correctly class fearful expressions out of the overall number of expressions that were predicted as being fear. As a result, boosting the precision score.

Performance evaluation of the models showed that the RUSBoosted tree ensemble classifier for frontal facial orientation returned similar weighted F_1 measure, precision and recall at 71%. This trend was similar for left profile with F_1 measure only slightly below at 70.84% compared to 71.39% and 72.28% precision and recall, respectively. The right profile achieved a weighted precision of 70.55%, and 69% for both recall and F_1 measure.

Table 8.5a, 8.5b and 8.5c: Performance summary of classifiers for the frontal, left and right profile facial views

Table 8.5a RUSBoosted tree ensemble classifier summary for the frontal facial orientation

	Number of expressions						
Class	TP	FP	FN	TN	Precision (%)	Recall (%)	F_1 measure (%)
Amuse	83	14	13	74	85.57	86.46	86.01
Sad	26	23	18	117	53.06	59.09	55.91
Fear	22	16	22	124	57.89	50.00	53.66
Weighted Average					71.1766	71.19565	71.0771

Table 8.5b SVM classifier summary for the left profile view

	Number of expressions						
Class	TP	FP	FN	TN	Precision (%)	Recall (%)	F_1 measure (%)
Amuse	85	20	11	68	80.95	88.54	84.58
Sad	32	21	12	119	60.38	72.73	65.98
Fear	16	10	28	130	61.54	36.36	45.71
Weighted Average					71.39	72.28	70.84

Table 8.5c LDA classifier summary for the right profile view

	Number of expressions						
Class	TP	FP	FN	TN	Precision (%)	Recall (%)	F_1 measure (%)
Amuse	79	20	17	68	79.80	82.29	81.03
Sad	28	27	16	113	50.91	63.64	56.57
Fear	21	9	23	131	70.00	47.73	56.76
Weighted Average					70.55	69.57	69.37

Tables 8.5a, b and c summarise the number of expressions that were considered true negatives, false positives, false negatives, true negatives. Furthermore, the precision, recall and F_1 measure (%) for 8.5a RUSBoosted tree ensemble classifier for the frontal facial orientation, 8.5b Support Vector Machine (SVM) classifier for the left profile and 8.5c Linear Discriminant Analysis (LDA) classifier for right profile side. The overall weighted-average *precision, recall, and F_1 measure are also given.*

Key: Amuse = Amusement; SVM = Support Vector Machine; LDA = Linear Discriminant Analysis; TP = True Positive; FP = False Positive; FN = False Negative; TN = True Negative

Degrees of Movement

A performance comparison of the classifiers, ranked the top 4 for the predictive accuracy recognition related to each facial orientation, is shown in Table 8.6. The best performing classifiers for the degrees of movement achieved greater than 70% accuracy. Classifier models for the frontal facial orientation outperforming the classification of spontaneous expressions from the profile sides of the face.

The best performing models for expressions from the frontal facial orientation were the SVM and Ensemble of bagged decision tree classifiers with equal accuracy of 75%. The SVM achieved the highest accuracy of 71.7% from the left profile sides, followed by the Simple Tree and LDA classifiers with a similar performance of 70.7% and 70.1% respectively, and the Ensemble of bagged decision tree achieving the lowest predictive accuracy score of 68.5% The LDA were the best performing models for the right profile sides achieving 71.1% recognition accuracy.

Table 8.6: Overall recognition accuracy of classifiers for emotional facial expressions

Landmark Degrees		SVM (%)	Simple Tree (%)	LDA (%)	Ensemble of bagged decision trees (%)
	Front	**75**	67.9	67.4	**75**
	Left	**71.7**	70.7	70.1	68.5
	Right	66.8	63.6	**70.1**	67.9

Table 8.6 shows the performance comparisons of the top four classifiers using landmark facial data for magnitude. The models using accuracy (%) as a metric for evaluating the true class.

Key: SVM = Support Vector Machine; LDA = Linear Discriminant Analysis; KNN = K- Nearest Neighbors

The confusion matrices for the top performing models for the frontal, left and right profile sides of the face were examined (Tables 8.7a, b and c). The confusion matrices for the top performing models for the frontal facial orientation demonstrated similar detection rates with 92/96 (96%) and 91/96 (95%) for amusement expressions classed by the SVM and Ensemble of bagged decision tree classifier, respectively. Furthermore, this accounted for 81% and 79% of the 114 and 115 predicted amusement expressions.

For the classification of the emotional expression of sadness, 22 (54%) and 26 (59%) sad expressions were correctly classed which also accounted for 67% and 70% of overall predictions of sadness. Fear expression was detected 22 (50%) and 21 (48%) out of 44 possible expression of fear and 65% and 66% of the 34 and 32 predictions of fear.

Likewise, for the left profile sides, confusion matrix for the SVM classifier shows that 85 out of 96 (89%) amusement images were correctly classified and accounted for 77% of the 110 predicted amusement expressions. Compared to sadness where 32 out of a possible 44 expressions of sadness (73%) were correctly classed and made-up 64% of the 50 predictions of sadness. Fear was detected but at very low levels, at 34% but made up 63% of the 24 predictions of fear.

For the classification breakdown for the right profile side shows that amusement was correctly classified 80/96 (83%) of time and accounted for 78% of overall predicted amusement expressions. Whereas 28/44 (64%) were correctly classed and made-up 55% of the 51 predictions of sadness. Recognition of fear was better at 48% and 21 out 30 (70%) prediction for fear were correct.

Table 8.7a, 8.7b, 8.7c and 8.7d: Confusion matrices for the best performing classifiers for the frontal, left and right profile facial views

Table 8.7a Confusion matrix for the frontal using the SVM classifier

True Classes	Class	Predicted Image Classes		
		Amuse	Sad	Fear
	Amuse	92	2	2
	Sad	10	24	10
	Fear	12	10	22

Table 8.7b Confusion matrix for the frontal view using the Bagged Trees classifier

True Classes	Class	Predicted Image Classes		
		Amuse	Sad	Fear
	Amuse	91	3	2
	Sad	9	26	9
	Fear	15	8	21

Table 8.7c Confusion matrix for the profile left side using the SVM classifier

True Classes	Class	Predicted Image Classes		
		Amuse	Sad	Fear
	Amuse	85	6	5
	Sad	8	32	4
	Fear	17	12	15

Table 8.7d Confusion matrix for the profile right side using the LDA classifier

True Classes	Class	Predicted Image Classes		
		Amuse	Sad	Fear
	Amuse	80	11	5
	Sad	12	28	4
	Fear	11	12	21

Tables 8.7a, b, c and d display a series of confusion matrices that illustrates the breakdown in recognition of images of three emotional facial expressions: amusement, sadness and fear. Each confusion matrix represents the top performing classifier for each facial orientation. The number of expressions that were correctly classified runs along the principal diagonal.

Key: Amuse = Amusement; SVM = Support Vector Machine; LDA = Linear Discriminant Analysis

Using the information derived from the confusion matrices the number of TN, FP, FN, TN for each expression class, as well as the precision, recall and F_1 measure were determined.

SVM and Ensemble of bagged decision tree classifiers for frontal facial orientation yielded similar weighted F_1 measure, precision at 74% and recall at 75%. This trend was similar for left profile with the F_1 measure only slightly below at 69.9% compared to 70.57% and 71.74% precision and recall, respectively. The right profile achieved a weighted precision of 70.39, 70.1% for recall, and a F_1 measure of 69.6%.

Amusement returned a high recall percentage ranging from 83% to 96%, for which the highest was obtained for the frontal facial orientation. Though it might be the result of the high detection rate of amusement, equally high number of incorrect predictions were made for amusement. Sadness yielded higher precision score for frontal but were better for recall of profile sides. Fear yielded higher precision than recall for all facial orientations. Again, this suggests that recognition of fear was moderately successful out of the total number of predicted expressions of fear, despite the low number of detections and therefore yielding reasonably good percentages for precision.

Overall, higher predictions and detection of sadness and fear increased precisions and recall for all orientations of the face. Models for emotional facial expression classification from the frontal facial orientation performed better than models classifying expressions from the profile sides of the face as determined by higher weighted precision (74%), recall (75%) and F_1 measure (74%). A graphical summary of the performance models is summarised in Tables 8.8a, b, c and d with the precision, recall and F_1 measure converted into percentages (%). This was done for the SVM and Ensemble of bagged decision tree classifiers for the frontal facial orientation, Support Vector Machine (SVM) classifier for the left profile and LDA classifier for the right profile side.

Tables 8.8a, 8.8b, 8.8c and 8.8d: Performance summary of classifiers for the frontal, left and right profile facial views

Table 8.8a SVM classifier summary for the frontal facial orientation

Class	TP	FP	FN	TN	Precision (%)	Recall (%)	F_1 measure (%)
Amuse	92	22	4	66	80.70	95.83	87.62
Sad	22	12	22	128	66.67	54.55	60.00
Fear	24	12	20	128	64.71	50.00	56.41
Weighted Average					73.52044	75	73.55152

Table 8.8b Ensemble of bagged decision tree classifier summary for the frontal facial orientation

Class	TP	FP	FN	TN	Precision (%)	Recall (%)	F_1 measure (%)
Amuse	91	24	5	64	79.13	94.79	86.26
Sad	26	11	18	129	70.27	59.09	64.20
Fear	21	11	23	129	65.63	47.73	55.26
Weighted Average					73.78214	75	73.56978

Table 8.8c SVM classifier summary for the left profile side

Class	TP	FP	FN	TN	Precision (%)	Recall (%)	F_1 measure (%)
Amuse	85	25	11	63	77.27	88.54	82.52
Sad	32	18	12	122	64.00	72.73	68.09
Fear	15	9	27	131	62.50	34.09	44.12
Weighted Average					70.56621	71.73913	69.88724

Table 8.8d LDA classifier summary for right profile side

Class	TP	FP	FN	TN	Precision (%)	Recall (%)	F_1 measure (%)
Amuse	80	23	16	65	77.67	83.33	80.40
Sad	28	23	16	117	54.90	63.64	58.95
Fear	21	9	23	131	70.00	47.73	56.76
Weighted Average					70.39129	70.1087	69.61725

Tables 8.8a, b, c and d display a series of table summary outlining the number of expressions that were considered true negatives, false positives, false negatives, true negatives. Furthermore, the precision, recall and F_1 measure (%) for 8.8a Support Vector Machine (SVM) and 8.8b Ensemble of bagged decision tree classifiers for the frontal facial orientation, 8.8c Support Vector Machine (SVM) classifier for the left profile and 8.8d Linear Discriminant Analysis (LDA) classifier for the right profile side. The overall weighted-average precision, recall, and F_1 measure are also given.

Key: Amuse = Amusement; SVM = Support Vector Machine; LDA = Linear Discriminant Analysis; TP = True Positive; FP = False Positive; FN = False Negative; TN = True Negative

8.2 Discussion

In contrast to the global flow extracted using the LK optical flow algorithm, which surmised all directional vectors emanating from the origin of the graph. The manual extraction of facial landmarks allowed the computation of flow activity at localised specific facial landmark points. This meant that mean vector magnitude values (pixel) and directional movement (angles˚) for all landmarks could be isolated.

Unlike optical flow where data were assigned into groups based on extent of movement. The mean vector magnitude for landmarks between expressions could be directly transferred onto an emotion map which schematically indicated the location and direction of action for each landmark. The emotion map is an adapted form of the compass graph with bearing range of 0° to 360° which is divided into 36 sectors of 10˚ angles. The default orientation where 0˚ is located East at the 3 o'clock position and rotating counterclockwise for increasing angles with 90˚ located at the top at the 12 o'clock position, 180˚ on the left (9 o'clock) and 270˚ degrees at the bottom (6 o'clock) positions. They display the average displacement of a landmark point with respect to the origin for each emotion directional movement falling in one of the 36 direction bins (10˚ segments).

Frontal view

It is important to note that right and left directional movements on emotion maps depict frontal facial views (Figure 8.2) correspond to movement directed towards the left and right sides of the subject's face, respectively. As vectors represent movement of facial expression occurring on the subject's face is projected onto the emotion map as perceived by the viewer. For example, vector movement orientation towards 0˚ (East) represent movements towards the left of the subject's face. Conversely vector movement orientation towards 180˚ (West) represent movements to the right of the subject's face.

During the expression of amusement, movement in the orbital areas were obtained from movement of facial landmarks: Exocanthion, Palpebral superius, Endocanthion and Palpebral inferius. Vector activity for the expression of amusement was a consequence of contraction of *orbicularis oculi (pars orbitalis)* [defined by AU 6, cheek raiser] causing the cheeks to rise. Furthermore, the actions of the *orbicularis oculi (pars palpebralis)* [defined by AU 7, lid Tightener] when contracted, pulls the upper and lower eyelids, and adjacent skin together towards resulting in vertical compression and horizontal lengthening of the eyes (Ekman *et al.*, 2002). For the expression of fear, vector movements were generally directed superiorly and ensued by a contraction of the *levator palpebrae superioris* [defined by AU 5, upper lid raiser] and *orbicularis oculi (pars palpebralis)* causing the upper eyelid to widen superiorly [defined by AU 7, lid Tightener] *(Kohler et al., 2004; Waller et al., 2008)*. This was also likewise seen for the expressions of sadness but to a lesser extent. The movements which were a consequent to contraction of the *orbicularis oculi*, causing downward tension beneath the lower eyelid [defined by AU 7, lid Tightener] and shortening of the eye fissure (Kohler *et al.*, 2004).

Movement in the forehead and upper facial regions was obtained from movements of the Trichion, Glabella, Sellion, outer, apex and inner eyebrows. For the expressions of fear, vector activity was directed vertically upwards which may be a consequence of activation of the *frontalis* muscle [defined by AU 1, inner brow raiser, and AU 2, outer brow raiser] in raising the eyebrows. Vector movement for the facial expression of sadness was due to the activity of the *frontalis (pars medialis)* and joint contraction of the *corrugator supercilii, depressor supercilii,* and *procerus* which caused the inner brows to be raised [defined by AU 1, inner brow raiser], and drawn medially [defined by AU 4, brow lower]. This contributed to lateral vector movement of the Exocanthion to decrease the eye fissure opening. Whereas for the expression of amusement, vector movements oriented inferiorly which may be due to contraction of *orbicularis oculi (pars orbitalis)* [defined by AU 6, cheek raiser] and *orbicularis oculi (pars palpebralis)* portion [defined by AU 7, lid tightener] which changes the orbit, recruiting movement in surrounding regions, drawing the eyebrows as well as the upper facial regions downwards.

Movement in the nasal and midfacial region included the following landmarks: Pronasale, right and left Alare, left and right Zygion, left and right Gonion. Vector movements of the left and right Zygion, left and right Gonion for amusement were directed superiorly at an oblique angle which is indicative of nostril flaring. This resulted from the contractions of the *zygomaticus major* [defined by AU 12, lip corner puller] and contraction of the o*rbicularis oculi (pars orbitalis)* [defined by AU 6, cheek raiser] pulling the cheeks upwards and outwards, subsequently increasing the width of the face. Furthermore, the contraction of *zygomaticus major* may have induced nostril flaring which is reflected by the vector movements outwards and upwards. This widening may have been heightened by the contraction of the *risorius* and *platysma*, causing the lips to stretch laterally [defined by AU 20, lip stretcher]. Equally, vector movement directed upwards at an oblique angle demonstrated in expressions of fear and sadness were attributed by the contraction of *levator labii superioris* [defined by AU 10, upper lip raiser] and dilation of the alar portion of the *nasalis* muscle [defined by AU 38, nostril dilator] for fear and sadness, respectively.

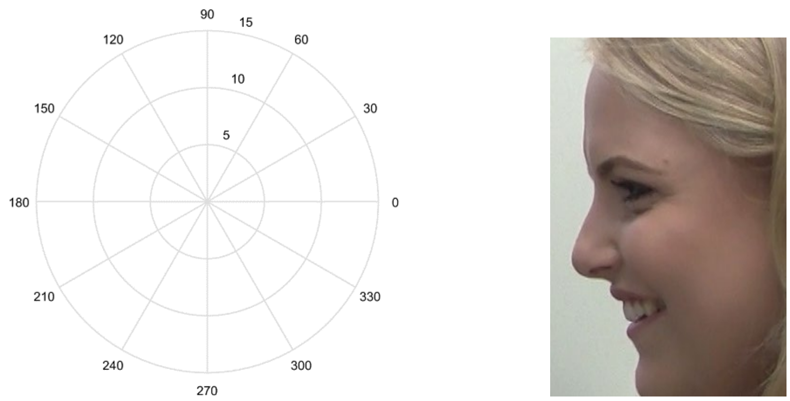
For the expression of amusement, all vector flow of the landmarks pertaining to the oral regions as indicated in the emotion maps were directed superiorly at oblique angles. Movement in these segments were a result of contractions of the *zygomaticus major* [defined by AU 12, lip corner puller] which caused lateral upward stretching of the corners of the lips, consequently, forcing the upper lip to ascend. For the expression of fear summation of vector flow were caused by a combination of contractions from the *risorius* and *platysma* [defined by AU 20, lip stretcher] resulting in lateral stretching of the lips. Also, relaxation of the *mentalis* or *orbicularis oris* [defined by AU 25, lips part] causing the entire upper lip to be raised upwards. For expressions of sadness, vector movements indicated by the emotion maps were directed superiorly and outwards, but to a lesser extent than the observed activity for amusement and in fear. This was unexpected considering contractions of the *depressor anguli oris* [defined by AU15, lip corner depressor], seen in 50% of sadness expressions would cause not only slight lateral outward movement but downward depression of the lips (Ekman *et al.*, 2002; Kohler *et al.*, 2004). A possible explanation could be that the movement of the *mentalis* [defined by AU 17, chin raiser] was greater than the activity exerted by the *depressor anguli oris* causing an overall elevation of the lips and surrounding regions.

Profile left view

As there were fewer landmarks on the profile sides (18) compared to frontal facial views (32) it was thought to have hindered success of differentiation. This was not evident in the emotion maps for the profile left side (Figure 8.3) where there was no directional overlap of vector movement between emotional expressions with the exception of two facial landmarks. At the Sellion between the expression of amusement and fear. Likewise, overlap in movement between the expression of sadness and fear at the Gnathion. This arrangement in pattern of activity meant that the profile view of the face may yield discriminatory power to differentiate between emotional expressions.

With respect to the orientation of the face, feature vector movement oriented between 90˚ to 270˚ to which represents movements towards either the anterior or medial portions of the face. Vector movement directed between 0˚ to 90˚ and 270˚ to 360˚ depicts movements towards either lateral or posterior portions of the face (Figure 8.5).

Figure 8.5: Emotion map associated with left profile facial expressions



(a) Emotion map template (b) Left profile - Amusement

Left / anterior Right/ posterior

Figure 8.5 displays (a) the emotion map template used to illustrate the orientation of feature vectors with respect to left profile view at specific landmarks. Image (b) is an example of a subject displaying the emotional expression of amusement. Permission granted for use of this image.

Movement of vectors for fear of the Palpebral superius was attributed by a contraction of the *levator palpebrae superioris* [defined by AU 5, upper lid raiser], which retracted the upper eyelid, causing it to orient towards the 50˚ to 60˚ sector. Furthermore, the tensing of the lower lid [defined by AU 7, lid Tightener] and depression of the lower eyelid downwards results in lateral movement of the Exocanthion towards the direction 170˚ to 180˚ and inferior retraction of the Palpebral inferius landmark the in the direction 330˚ to 340˚ sector.

Movement of vectors for sadness in the orbital regions were dispersed between 100˚ to 110˚, 160˚ to 170˚ and 180˚ to 190˚ for the Palpebrae superius and inferius, and Exocanthion, respectively. The movements reflect closing of the eyelids due to the anterior projections of vector. Additionally, anterior projections of the apex and inner portions of the eyebrow laterally between 180˚ to 190˚ may reflect the activity of *corrugator supercilii, depressor supercilii* and *procerus,* which draws the eyebrows medially and downwards [defined by AU4, brow lower]. However, the contraction of *frontalis (pars medialis)* [defined by AU 1, inner brow raiser] raises the inner portion observed in the frontal view was not evident.

Similarly, for the expression of amusement, vectors in the orbital region directed laterally and inferiorly, as reflected activity was constrained within 210˚ to 220˚, 150˚ to 160˚ and 200˚ to 210˚ for the Palpebral superius and inferius, and Exocanthion landmarks, respectively. This was attributed to by a contraction of the orbital [defined by AU 6, cheek raiser] and the palpebral [defined by AU 7, lid Tightener] regions of the *orbicularis oculi* which caused depression of upper eyelid and elevation of lower eyelid to constrict the eye aperture.

Movement in the forehead and upper facial regions comprised of the following landmarks: Trichion, Glabella, Sellion, Outer, apex and inner eyebrows. For the expressions of fear, the outer brow was observed to be slightly elevated along with anterior vector movement which supports activity of the Frontalis (AU 1, inner brow raiser and AU 2, outer brow raiser) to the eyebrows. However, it does not explain movement of Trichion, Glabella and inner and apex brow regions in which vector activity were directed posteriorly indicating retraction of landmark points. A possible explanation could be the variability of activity between subjects cause discrepancy in mean displacement.

Likewise, for sadness, vector movements were oriented upwards and anteriorly between the compass directions of 140˚ of 190˚. Activity may be attributed by the contraction of the *frontalis (pars medialis)* with the *corrugator supercilii, depressor supercilii and procerus* which caused the inner brows to be raised [defined by AU 1, inner brow raiser], and be drawn medially [defined by AU 4, brow lower]. For the expression of amusement, vector movements of the Trichion were directed superiorly which can reflect increase lengthening of the face. Landmark representatives of the upper portion and brow regions were oriented laterally and slightly inferior towards the anterior direction within the narrow regions between 180˚ to 220˚. Possibly related to the contraction of the *orbicularis oculi* which draws skin towards the eye from the temple and cheeks which subsequently draws surrounding regions such as the eyebrows inferiorly.

Movements in the nasal area included the following landmarks: Pronasale, right and left Alare. For the emotional expressions of amusement, sadness and fear, minimal vector movements were observed and directed superiorly with the exception of the Pronasale for amusement. General upwards movements may be due to the contractions of the *zygomaticus major* [defined by AU 12, lip corner puller] for the expression of amusement, contraction of *levator labii superioris* [defined by AU 10, upper lip raiser] for fear and dilation of the alar portion of the nasalis muscle [defined by AU 38, nostril dilator] for sadness. All of which induced nostril flaring. These patterns were similarly observed for the right profile side.

Movement in the oral and lower portions of the face was reflected by vector movements for the facial landmarks: Labiale superius and inferius, Chelion. The summation of vector movement that occurred for these landmarks for the expression of amusement, were orientated superiorly and narrowly angled between 40˚ to 50˚. This movement was related to the contraction of the *zygomaticus major* [defined by AU 12, lip corner puller] resulting in lateral upward stretching of the corners of the lips. For the expression of sadness, movement in the oral area of the face was reflected by vector movements orientated superiorly and laterally in the direction 70˚ to 80˚ and 20˚ to 30˚ for the Labial superius and Chelion, indicative of elevation of the upper lip. Vector movements oriented inferiorly and anteriorly towards the directions of 240˚ to 250˚ for the Labiale inferius was related to the contraction of the *mentalis* [defined by AU 17, chin raiser] which protrudes the lower lip causing the Labiale inferius to arch downwards.

For the emotional expression of fear, summation of vector flow in the oral area were caused by a combination of the forced opening and stretching of the mouth by muscles that act in opposition to muscles that close the jaw [defined by AU 27, mouth stretch] and the contraction of the *Risorius* and *Platysma* [defined by AU 20, lip stretcher] to draw the lips back horizontally. These actions cause the entire upper lip to be raised upwards, this is reflected by vector movements orientated vertically in the compass direction of 70˚ to 90˚ for the Labiale superius and Chelion landmarks and extreme displacement of the Labiale inferius landmark anteriorly towards the direction of 190˚ to 200˚.

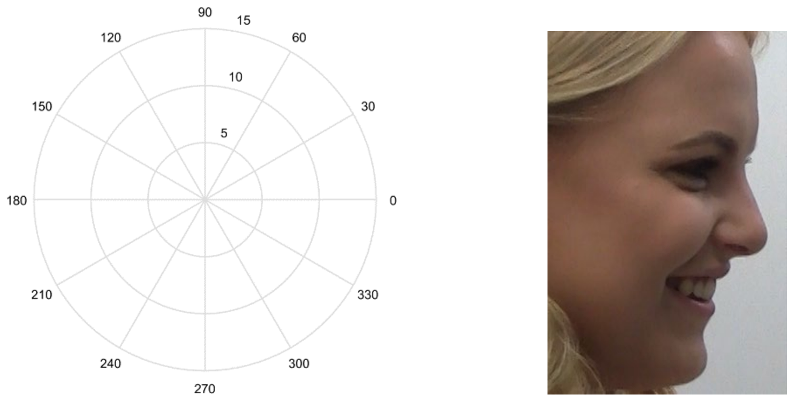
Movement in the lower facial regions were obtained from movements in landmarks Supramentale, Pogonion, and Gnathion. For the expression of amusement, vector movements were orientated inferiorly between 250˚ to 300˚ due to the relaxation of the *mentalis* or *orbicularis oris* [defined by AU 25, lips part], which parts the lips and lowering of the jaw to elongate the face (Waller *et al*., 2008).

Conversely, the expression of sadness, vector movements were orientated superiorly and anteriorly towards the map regions 100˚ to 160˚. The cause of the activity results from the contraction of the mentalis [defined by AU 17, chin raiser] which raises the chin and subsequently shortens the length of the face. For the expression of fear, anterior vector movement of the Pogonion exerted towards 200˚ to 210˚, meaning outwards. This was due to the contraction of the *mentalis* [defined by AU 17, chin raiser] which caused the chin to bulge as it retracted. Similarly, this activity caused vector movements directed upward in the direction of 80˚ to 90˚and 100˚ to 110˚ for the landmarks, Supramentale and Gnathion as a consequent of the pulling of the *mentalis*.

Profile Right

It was speculated that emotion maps (Figure 8.4) illustrating movements in the profile right would mirror the vector movements for the profile left view. As such vector movements generated in the directions between 0˚ to 90˚ and 270˚ to 360˚ represent anterior or medial movements, and directional vectors between 90˚ to 270˚ represent lateral movements in the direction towards the side of the face (Figure 8.6).

Figure 8.6: Emotion map associated with right profile facial expressions



(a) Emotion map template **(**b) Right profile - Amusement

Left/ posterior Right/ anterior

Figure 8.6 displays (a) the emotion map template used to illustrate the orientation of feature vectors with respect to the right profile view. Image (b) is an example of a subject displaying the emotional expression of amusement. Permission granted for use of this image.

Movement of vectors for fear in the orbital regions were orientated superiorly between 60˚ to 140˚. These activities could be explained by the contraction of the *levator palpebrae superioris* [defined by AU 5, upper lid raiser], which retracted the upper eyelid, and the tensing of the lower lid [defined by AU 7, lid Tightener]. Movement of vectors for sadness in the orbital regions were directed laterally towards 350˚ to 10˚ for the Palpebrae superius and Exocanthion, which reflects anterior movements from the closing of the eyelids. Similarly, to fear, the tensing of the lower lid [defined by AU 7, lid Tightener] caused vectors for the Palpebral inferius landmark vertically in the directions of 80˚ to 90˚.

For the expression of amusement, upwards and downwards deflection of Palpebrae inferius landmark towards 30˚ to 40˚ and superius landmarks towards the direction of 320˚ to 330˚, respectively. Furthermore, vector movements representative of Exocanthion were laterally oriented towards 0˚ to 10˚. This may be indicative of movements caused by the contraction of the *orbicularis oculi (pars orbitalis)* [defined by AU 6, cheek raiser] and *orbicularis oculi (pars palpebralis)* [defined by AU 7, lid Tightener]. As a result, depression of upper eyelid and elevation of lower eyelid to constrict the eye aperture.

Mirroring projections observed on the profile left view, movement in the forehead and upper face for the expressions of fear were directed upwards for Glabella, Sellion, inner and apex of the brow which had activity constrained within 20˚ to 110˚. The vector movements could be explained by the simultaneous contraction of the *frontalis* (AU 1, inner brow raiser and AU 2, outer brow raiser) which raises the eyebrows causing the anterior directed movements. Likewise, for sadness, elevated vector movements were oriented superiorly between the compass directions of 20˚ to 140˚. The upwards movement may be attributed by the contraction of the *frontalis (pars medialis)* which caused the inner brows to be raised with slight depression and anterior movement of the outer brow may be a related concomitant effect. For the expression of amusement, vector movements of the Trichion oriented superiorly reflect increase lengthening of the face. Landmarks representative of the upper portion and eyebrow regions were oriented laterally and slightly inferior towards the anterior direction. This may be related to movements of *orbicularis oculi* which draws skin towards the eye from the temple and cheeks which subsequently draws surrounding regions such as the eyebrows inferiorly.

The summation of vector movement that occurred for the oral regions for the expression of amusement, were directed superiorly angled narrowly within 120˚ to 140˚. The resultant angle of the movement was due to the contraction of the *zygomaticus major* [defined by AU 12, lip corner puller] which draws the angle of the lips upwards and posteriorly. However, vector activity for the Pogonion and Gnathion were orientated along the horizontal plane to the direction of 310˚ to 320˚ and 0˚ to 10˚ respectively and reflect movement anteriorly. Supposedly a consequence of the residual movements caused by the stretching of the lips *zygomaticus major* [defined by AU 12, lip corner puller] and relaxation of the *mentalis* or *orbicularis* [defined by AU 25, lips part] which protrudes the chin forwards.

For the emotional expression of sadness, vector movements orientated upwards and anteriorly at an oblique angle towards 30˚ to 40˚ was observed for the Labial superius and inferius, and inferiorly towards 260˚ to 270˚ for the Chelion. This may be related to the pursing of the lips [defined by AU 23, lip tightener] which was seen in some subjects and the contraction of the *depressor anguli oris* [defined by AU 15, lip corner depressor] which draws the lips together, depressing the Chelion as it pulls the corner of the lips downward. The contraction of the *mentalis* [defined by AU 17, chin raiser] aids in raising the Labiale inferius and subsequently, Labiale superius. Furthermore, this action of the *mentalis* protrudes the chin upwards and outwards explaining activity movements of the Supramentale and Pogonion in the lateral direction between 350˚ to 0˚.

During the expression of fear, movement in the oral area was caused by a combination of the force opening [defined by AU 27, mouth stretch] from the actions of lateral *pterygoid* and *digastric* muscle to depress the mandible; and stretching of the mouth [defined by AU 20, lip stretcher] due to contractions of the *risorius* and *platysma*. As a result, the retraction of the Labiale inferius and supramental in the direction of 200˚ to 210˚ and 140˚ to 150˚, respectively; raising of the upper lip as reflected by vector movements in the compass direction of 30˚ to 40˚ and 70˚ to 80˚ for the Labiale superius and Chelion, respectively. Anterior vector movement of the Pogonion and Gnathion landmarks in the direction of 330˚ to 340˚ and 10˚ to 20˚ through the activity of the mentalis [defined by AU 17, chin raiser] which caused the chin to bulge and protrude.

Classification

Classification was performed on the obtained feature vectors pertaining to mean vector magnitude and angle of direction in separate analysis for the frontal, left and profile facial views. The overall accuracy recognition of the classifiers in predicting the class expressions of amusement, sadness and fear were provided. Where the predictive accuracy applies to the correct number of emotional expressions that were correctly classed out of the total number of expressions classed in the same emotion category. A comparison was made between classifiers to identify the classifier with the highest predictive accuracy recognition rate.

In contrast to optical flow analysis, slight improvements in emotional facial expression recognition were observed. Emotion classification using feature vectors from landmarks revealed consistency in overall recognition across the board for various facial orientations for precision, recall and F_1 measure. It was shown that facial expression recognition from the frontal view using the RUSBoosted tree ensemble or SVM classifier achieved accuracy recognitions between 73.5 to 75% for recall, precision, and F_1 measure using features pertaining to directional data. Compared to recognition using features relating to magnitude data using the Ensemble of bagged decision tree classifier could achieve up to 71% accuracy. When it came to the effect of pose variation on expression recognition, there were no differences in recognition accuracy as a function of view. Similar precision, recall, and F_1 measure were achieved for the left and right profile views using features pertaining to either magnitude or directional data. The recognition ranged between 70.8 to 72.3% and 69.4 to 70.55% using magnitude data for the left and right profile views, respectively. For directional data, recognition ranged between 69.9 to 71.7% for the SVM and 69.4 to 70.55% for the LDA classifier for the left and right profile views, respectively.

Similarly, to LK optical flow, it was observed that amusement had the highest recognition of up to 95.8% for recall and 87.6% for F_1 measure. Followed by sadness achieving a maximum of 72.7% and 66% for recall and F_1 measure respectively. Fear was detected at much higher levels (F_1 measure of up to 56.8%) compared to optical flow (F_1 measure of up to 30.5%) which may have attributed to the overall stability of precision, recall and F_1 measure. Furthermore, where amusement was consistently classified across all view, sadness was classified best from the left profile view, and fear was classified best at profile right view.

The results indicated that recognition of emotional expression was not negatively affected when viewed from the profile sides. This may be due to that the profile sides have the ability to accentuate the movements of the regions such as the oral and orbital regions that were heavily implicated in the emotional facial expressions observed. This was evident in the directional vector activity on the emotion maps representing landmark activity of the left and right profile sides. Therefore, the feature vectors depicting profile facial activity showed potential for differentiating between emotions because it may highlight areas not captured in the frontal facial orientation that might be of relevance, warrant further investigation.

Overall performance of classifying facial expressions using facial landmarks achieved greater recognition accuracy than the LK optical flow. This might have been due to the manner in which the algorithm was implemented in this study. The LK optical flow algorithm was used to compute global deformation changes on the face during an expression. The algorithm then quantified all vectors into sectors based on absolute direction of movements around a compass. Meaning that, irrespective of location, if the resulting motions were in the same directions, they were aggregated together. This property made it difficult to discern the relative contribution of individual facial features toward each emotional expression. Furthermore, the algorithm only generated 12 feature vectors which may have been insufficient to model the statistical correlation of the features. Thereby producing an underfit model resulting in low expression recognition.

In contrast, the feature vectors in the landmark analysis articulated movements at different landmark points and thus was able to generate more feature vectors. One important distinction was the manual annotation of landmarks in images that required manually labelling the feature points of the mouth, eyes, and eyebrows. This localising of features contributed to an increase in accuracy over measuring global facial flow movement. As the prediction of emotional facial expressions in machine learning are dependent on the training data provided, due to the subtlety of naturally occurring expression it was pertinent to minimise the margin of error where possible so that expression recognition truly reflected activity movement.

Overall, the SVM classifier achieved better classification results using the feature data. Whereas LDA and bagged decision trees can perform multiclass classification without resorting to pairwise comparison, SVM classifier is a binary classifier in that it aims to separate two different categories of data (Ghimire & Lee, 2013). When dealing with greater than two classes, multiple binary classifiers are trained, with the class output determined using a majority class voting for all classifiers (Michel, 2003). This may indicate that the characteristics of the features for emotional facial expressions might be better suited for binary classification rather than discriminating all amongst each other. Although SVM has been known to generally work well with small sample data (Michel, 2003) like in this case, classification of large data is problematic due to the increase in training time and computation complexity of the algorithm (Cervantes *et al.*, 2007). This will have to be taken into consideration for future automatic framework designs on emotional facial expression recognition.

Chapter 9 – Research limitations, recommendations, and conclusion

9.1 Research limitations and recommendations

Although this study has several significant contributions to our understanding of how individual differences and beliefs shape their emotional expressiveness, the findings of the study are qualified by certain limitations in its design and analysis that are worth mentioning.

Sample Size

First, the study dealt with a relatively small sample size, with disproportionate numbers of negative emotions to positive emotion images as well as in the gender category. This prevented further investigations into effects of gender and ethnicity on emotional facial expressions and should be considered in future research. Furthermore, assessment of other intrinsic factors such as age-related changes to improve model patterns for expression recognition.

Emotion Inducing Medium

Although the use of films is advantageous in terms of experimental control (e.g., vs. idiographic methods of emotion elicitation such as reliving an emotional memory), the selection of the film clips utilised for emotion induction was dependent on the likelihood of evoking pre-determined emotions and subsequent expressive behaviours. Whilst films were successful at eliciting emotional experience of amusement and sadness, they were less successful at inducing emotional experience of fear. Moreover, this did not translate to the level of behavioural expression as the elicitation of emotional facial expression was moderately successful for amusement and less successful for sadness and fear. Previous exposure to the selected film clips may have decreased the emotional impact of the stimulus and subsequently reduced emotional display further resulting in disparity in images obtained. Due to the variability in perception where the emotion eliciting stimulus must be re-evaluated to select films or the use of multiple films within the same emotion category elicit the desired emotion.

Second, the study only utilised one exemplar of amusement, fear, and sadness for each participant. Previous studies (Kilincer, 2011; Siwan, 2015; Chow, 2019) had issues concerning individual difference in emotional regulation which accounted for the variability in perception of the films and emotional expression. This limited the number of facial images extracted. Furthermore, several multiple emotions were reported, from the variability in perception. Since one cannot control the circumstances of experience, suggests the use of multiple films would be more effective in eliciting the desired emotion.

Demand Characteristics

Another concern was the use of “demand” characteristics. This involves the participants being aware of what the researcher is investigating and therefore influences how participants are expected to behave (McCambridge *et al*., 2012). Upon further explanations of the experiment protocol to the volunteers, such as rating their emotional responses to the films, made it transparent that the premise of the study was to elicit emotions. It was possible that subjects responded with the emotions, they thought the film was intended to produce. Future studies may consider controlling for possible “demand” effects using the Marlowe–Crowne’s Social Desirability Scale (MC-SDS) (Crowne & Marlowe, 1960; Ribas *et al*., 2004) to verify whether emotion manipulation caused some alteration in the social desirability of the volunteers (Ribas *et al*., 2004; Moura, & Hutz, 2004).

Behavioural Expressions

One limitation in the use of films was the creation of mood states which were marked by progressive changes. This would have an effect on the baseline condition and thus elevate the threshold with which the movement of facial response would occur. This was seen in particular with sadness where most participants showed progressive drooping of the eyelids and maintenance in contraction of eyebrows whilst watching the sad stimulus. This difference in facial baseline could further reduce configuration quality of the observed facial expression.

Despite subjects being seated, distinct movement patterns and postural behaviour associated with emotions were observed. These natural bodily and head movements that accompanied the emotional expressions were direct causes for the images to be out of focal plane from one another. This created issues when cropping control baseline and expression images to congruent dimensions. When intense emotions were felt, extreme reactions ensued e.g., sadness stimulus induced crying behaviours and both the fear and sad stimulus created avoidance behaviours resulting in movement artefacts. Darwin (1872) regarded emotions as innate pre-disposition to act adaptively to increase chances of survival. This suggests in addition to facial expressions, body specific contributions for each emotional state are part of the proper adaptive responses. Therefore, future studies may benefit from multimodal analysis integrating body specific contributions to emotion expression which may enhance recognition.

Physiological Assessment

Another limitation was the use of a single physiological parameter to substantiate the occurrence of emotion. Although EDA has often been used as an index marker of emotional states, skin conductance response (SCR) may not always occur in response to emotive stimuli. Even in the absence of emotional arousal, responses can reflect output of physiological stress, cognitive and attentional processes (Braithwaite *et al*., 2013; Melander *et al*., 2017). Furthermore, EDA may be affected by environmental factors, such as temperature, humidity, and gross movement (Kalfa *et al*., 2002). Future research therefore would benefit greatly from assessing changes from multiple physiological signals (i.e., finger temperature, heart rate variability, respiration etc.) capturing both sympathetic and parasympathetic divisions of the ANS which subserve emotional processes. This is to ensure greater convergences of emotional states and to make more meaningful analysis the induction of an emotional state.

Self-report questionnaires

The drawbacks on the use of adjectives on a questionnaire to describe the type of emotion of experience are assumed to involve consciously accessing an emotional state and may prime the subjects into generating response that are viewed favourably by the majority and could compromise the validity of the assessment (Kreitchmann *et al.*, 2019). Future studies may alternatively adopt an open-ended or free labelling format where the subject list the emotions felt, and this may increase specificity of interpreting generated emotions.

9.2 Conclusion

This was an exploratory study aimed to identify behaviour patterns of facial movements most frequent in amusement, sadness, and fearful expressions. The study included the following specific aims: (1) To induce naturally occurring emotional responses in individuals. It was hypothesised that the use of short film clips would induce discrete facial expressions of discrete emotional states. (2) To validate presence of instigated emotions as revealed through facial expressions using self-reports and electrodermal activity (EDA). It was further hypothesised that coordination between expressive behaviour, and physiological responses should improve the reliability and precision of the elicited emotion facial expressions. (3) To classify and interpret facial activity data. The hypothesis was that the patterns of facial expressions of emotions were unique in that, they could be differentiated, furthermore classified from invariant views such as: frontal, profile left and profile right facial orientation.

Subjects were video recorded watching three emotion inducing short films. It was hypothesised that the use of short film clips would induce naturally occurring emotional facial responses of discrete emotional states. As this research intended to reflect the true nature of facial expressions, it was important to validate the presence of instigated emotions as revealed through facial expression by the use of self-reports and electrodermal activity (EDA). It was further predicted that coordination between expressive behaviour, and physiological responses should improve the reliability and precision of emotion facial expressions detected.

Subjective reports on experience of emotions indicated that the short films successfully elicited amusement and sadness, from their respective stimulus in majority of participants but was only moderately successful for fear. Furthermore, the use of EDA as the sole physiological parameter to substantiate the occurrence of emotion proved weak. SCR was observed during the expressions of amusement and fear whilst mixed responses pattern was seen for sadness. These SCR responses to sadness were marked by decreases in EDA, seen as both the presence and absence of SCR.

An important aspect in conducting an emotion inducing experiment is the ability to evoke emotion at a level of behavioural expression, it was observed that not all emotional expression were equally easy to elicit using films. Out of the 142 participants, a total of 184 appropriate facial expressions were elicited from 426 short film viewings across 111 subjects. Whilst facial expressions for amusement were successfully induced in 68% of subjects, the two negative emotions, sadness, and fear, were less successful. Facial expressions for these emotions were only elicited in 31% of the volunteers. When it came to behavioural level of expressions males were reluctant to express negative emotions as were participants of Asian compared to European ancestry. One explanation for the variation in emotional responses may be attributed to the ways in which the individual appraises the stimulus. Given the context of the study, how the subject evaluates the films as having personal meaning or relevance is a major factor contributing to the nature of the ensuing emotion.

Regarding expressive displays of amusement, sadness, and fear, variations within each emotional category, across individuals were observed. However, the study did however find a set of facial movements or AUs that were consistent and specific to each emotion category. Furthermore, these were recognisable across a diverse group of subjects supporting that these expressions were culturally invariant. The displays of amusement frequently included raised lip corners (AU 12, 96%), raised cheeks (AU 6, 92%), lid tightening (AU 7, 59%), and mouth opened (AU 25, 53%). Characteristic sad expressions comprised furrowed eyebrow from inner brows raised (AU 1, 52%) and drawn together (AU 4, 61%), lip corners stretched and turned down (AU 15, 50%), and chin raised (AU 17, 41%). Recognition of fearful faces was most highly associated with inner (AU 1, 57%) and outer eyebrows raised (AU 2, 39%), brow lowering (AU 4, 39%), raised upper lid (AU 5, 57%), tensed lower lids (AU 7, 39%), mouth opened (AU 25, 55%) and stretched (AU 20, 36%).

In amusement, an observed clustering of AU 6 with 7 (65%), and 12 (58%), AU 12 with 6 (79%), and AU 25 (49%); to lesser extend for sadness, clustering of AU 15 with 17 (18%), AU 1 and 4 with AU 15 (27%) or AU 17 (20%); in fear, AU 1 with 5 (57%), AU 1 with 2 and AU 5 (27%), AU 20 with 25 (25%).

The second stage required evaluation of facial images to deduce compact feature representations of emotions. This involved analysis of images for changes in movement between neutral/baseline and images of expression using two different methods of motion estimation to extract features: LK optical flow and landmark analysis using MATLAB (R2017b, version 9.3, USA). The LK optical flow analysis estimated global flow of the face, including computing explicit measurement of surface texture and features such as wrinkles, whereas for the analysis of landmark involved computing flow activity of facial movements at specific landmark feature points of the face.

The aim of feature vector analyses was to detect patterns and trends to discriminate the three emotional facial expressions. It was hypothesised that the patterns of facial expressions of emotions were unique and could be differentiated, furthermore classified from invariant poses such as: frontal, profile left and profile right facial orientation. As such that observed trends would be applied to expand the work towards automating detection of facial expressions of affective states. This becomes even more important in real world applications where successful recognition of facial expressions from facial areas not limited to whole face would reduce processing time where face orientation relative to the camera are not necessary to be in-plane with full frontal view.

Emotion maps were produced using the feature vector output to uncover patterns and trends that differentiate between the emotional expressions. The emotion maps indicated that greater facial activity was observed from emotion maps representing the frontal rather than profile views, with fear yielding overall greater intensity of movement. However, this did not negatively affect emotion recognition from the profile sides where classification of landmark feature vectors was consistent between the frontal and profile views, and in optical flow. Profile images yielded greater expression recognition accuracy than frontal facial orientation. This indicates that invariant poses have potential in differentiating between emotions because it may highlight areas not captured in the frontal facial orientation. This ability to detect changes in intensity of facial movements from non-frontal views with enough discriminating power for emotional expressions recognition has important implication for real world applications.

Feature extraction using the optical flow algorithm was limited in its ability to discriminate between emotional facial expressions due to the use feature vectors deduced from summation of global facial activity. As such the distribution of global vector activity did not vary between expressions, this property made it difficult to discern which features contributed towards the expression resulting in poor expression recognition. Feature vector representation from optical flow shows high discrimination for amusement of up 94.8% recall accuracy and F_1 measure of 80.2%, moderate recognition of sadness achieving up to 72.7% and 68.1% for recall and F_1 measure, respectively. But poor recognition for fearful expressions that obtained a 20.5% recall and 30.5% for F_1 measure at most. This resulted in overall fluctuations in accuracy, precision, and F_1 measure managing between 48.5 to 64.1%, 60.1 to 68, and 64.2 to 68% for the frontal, left and right profile facial views, respectively.

Contrary to expectations, emotional facial expression classification using feature vectors extracted from landmarks analysis achieved higher and consistent overall recognition across the board for precision, recall and F_1 measure achieving between 71.1 to 75%, 69.9 to 72.3% and 69.6 to 70.55% for the for the frontal, left and right profile facial views, respectively. Despite achieving reasonable recognition rates, classification of individual emotions showed that recognition of amusement was much greater in comparison to the recognition of fear and sadness which drove to increase the overall recognition rate. Where amusement was consistently classified across all views, achieving a recall and F_1 measure of up to 95.8% and 87.6% respectively. Sadness was classified best in profile view (72.7% recall and 66% F_1 measure), and fear was classified best at profile right view (56.8% recall and 47.7% F_1 measure). Though this was hindered by small sample sizes in the fear and sadness emotion category and thus the need for greater sample sizes of even class number to substantiate results. Nonetheless, these results indicate discriminating power for recognition comparable to current laboratory FER system. The distinction between amusement and negative emotions resulted in >80% detection accuracy underlines the capability of the developed systems for real world surveillance. Therefore, the use of landmarks serves as a reasonable starting point for further research to assess emotional facial expressions.

Future research will extend to eliciting not only universal emotions such as anger, contempt and disgust, but the more complex emotional states that involve aggregates of two or more emotions (such as fear/tension or fear/anxiety) to determine to which degree these appearances vary or overlap. Additionally, research into algorithms to detect and track specific features automatically as such to be streamlined into the classification process. This will circumvent problems associated with obtaining images with expressions where certain features were out of the focal plane due to overt bodily behaviour by allowing extrapolation of this facial activity.

Due to the severity of crimes from ASB has led to advancements in enhancing security and surveillance systems. As such there is a growing interest in developing automated detection methods for video surveillance systems to detect suspicious behaviour (Grant & Williams, 2011; Wiliem *et al*., 2011) as exhibited by non-verbal indicators of criminal intent. Although human vision can recognise facial expressions virtually without effort or delay. Facial expression recognition presents a challenging problem in the field of image analysis and computer vision. Recognition of spontaneous emotional facial expression with a high degree of accuracy remains difficult because of the subtlety, complexity, and variability of facial expressions.

As emotional expressions provide information to conspecifics, about antecedent events, concomitant responses, and probable next behaviour. It is proposed that findings for emotion specific facial activity will facilitate a research trajectory to expanding the scope of studies for investigations into expressions of persons displaying antisocial tendencies. By doing so, propel applications of facial expression recognition systems towards security surveillance, especially CCTV in the prediction and prevention of anti-social and other criminal behaviours.

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Appendices

Permission statement for use of basic emotional facial images

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Likert Questionnaire

Never Say No to Panda (2010) Directed by Advantage Marketing & Advertising

Time	**Scene 1**
00:00:41 - 00:00:53	At the office, Panda pushes all the computer equipment off the desk and starts hitting the table with the keyboard.

Amusement	0	1	2	3	4	5	6	7	8
Anger	0	1	2	3	4	5	6	7	8
Arousal	0	1	2	3	4	5	6	7	8
Confusion	0	1	2	3	4	5	6	7	8
Contempt	0	1	2	3	4	5	6	7	8
Contentment	0	1	2	3	4	5	6	7	8
Disgust	0	1	2	3	4	5	6	7	8
Embarrassment	0	1	2	3	4	5	6	7	8
Fear	0	1	2	3	4	5	6	7	8
Happiness	0	1	2	3	4	5	6	7	8
Interest	0	1	2	3	4	5	6	7	8
Pain	0	1	2	3	4	5	6	7	8
Relief	0	1	2	3	4	5	6	7	8
Sadness	0	1	2	3	4	5	6	7	8
Surprise	0	1	2	3	4	5	6	7	8
Tension	0	1	2	3	4	5	6	7	8

Never Say No to Panda (2010) Directed by Advantage Marketing & Advertising

Time	**Scene 2**
00:01:04 - 00:01:22	Panda appears in the kitchen and spills the liquid onto the bench, then starts pounding the flour.

Amusement	0	1	2	3	4	5	6	7	8
Anger	0	1	2	3	4	5	6	7	8
Arousal	0	1	2	3	4	5	6	7	8
Confusion	0	1	2	3	4	5	6	7	8
Contempt	0	1	2	3	4	5	6	7	8
Contentment	0	1	2	3	4	5	6	7	8
Disgust	0	1	2	3	4	5	6	7	8
Embarrassment	0	1	2	3	4	5	6	7	8
Fear	0	1	2	3	4	5	6	7	8
Happiness	0	1	2	3	4	5	6	7	8
Interest	0	1	2	3	4	5	6	7	8
Pain	0	1	2	3	4	5	6	7	8
Relief	0	1	2	3	4	5	6	7	8
Sadness	0	1	2	3	4	5	6	7	8
Surprise	0	1	2	3	4	5	6	7	8
Tension	0	1	2	3	4	5	6	7	8

Never Say No to Panda (2010) Directed by Advantage Marketing & Advertising

Time	**Scene 3**								
00:01:54 - 00:02:02	Panda kicks the spilt groceries and then proceeds to jump on them.								
Amusement	0	1	2	3	4	5	6	7	8
Anger	0	1	2	3	4	5	6	7	8
Arousal	0	1	2	3	4	5	6	7	8
Confusion	0	1	2	3	4	5	6	7	8
Contempt	0	1	2	3	4	5	6	7	8
Contentment	0	1	2	3	4	5	6	7	8
Disgust	0	1	2	3	4	5	6	7	8
Embarrassment	0	1	2	3	4	5	6	7	8
Fear	0	1	2	3	4	5	6	7	8
Happiness	0	1	2	3	4	5	6	7	8
Interest	0	1	2	3	4	5	6	7	8
Pain	0	1	2	3	4	5	6	7	8
Relief	0	1	2	3	4	5	6	7	8
Sadness	0	1	2	3	4	5	6	7	8
Surprise	0	1	2	3	4	5	6	7	8
Tension	0	1	2	3	4	5	6	7	8

Never Say No to Panda (2010) Directed by Advantage Marketing & Advertising

Time	**Scene 4**
00:02:16 - 00:02:26	Panda is staring at the man, he nudges his son to grab another cheese product and so the Panda moves out of the way.

Amusement	0	1	2	3	4	5	6	7	8
Anger	0	1	2	3	4	5	6	7	8
Arousal	0	1	2	3	4	5	6	7	8
Confusion	0	1	2	3	4	5	6	7	8
Contempt	0	1	2	3	4	5	6	7	8
Contentment	0	1	2	3	4	5	6	7	8
Disgust	0	1	2	3	4	5	6	7	8
Embarrassment	0	1	2	3	4	5	6	7	8
Fear	0	1	2	3	4	5	6	7	8
Happiness	0	1	2	3	4	5	6	7	8
Interest	0	1	2	3	4	5	6	7	8
Pain	0	1	2	3	4	5	6	7	8
Relief	0	1	2	3	4	5	6	7	8
Sadness	0	1	2	3	4	5	6	7	8
Surprise	0	1	2	3	4	5	6	7	8
Tension	0	1	2	3	4	5	6	7	8

Have you seen this short before? Yes / No / Can’t Remember (circle one)

Last Minutes with Oden (2009) Directed by Eliot Rausch

Time	**Scene 1**
00:01:20 - 00:01:35	The dog owner is sitting on the couch, he is talking on the phone and starts to cry

Amusement	0	1	2	3	4	5	6	7	8
Anger	0	1	2	3	4	5	6	7	8
Arousal	0	1	2	3	4	5	6	7	8
Confusion	0	1	2	3	4	5	6	7	8
Contempt	0	1	2	3	4	5	6	7	8
Contentment	0	1	2	3	4	5	6	7	8
Disgust	0	1	2	3	4	5	6	7	8
Embarrassment	0	1	2	3	4	5	6	7	8
Fear	0	1	2	3	4	5	6	7	8
Happiness	0	1	2	3	4	5	6	7	8
Interest	0	1	2	3	4	5	6	7	8
Pain	0	1	2	3	4	5	6	7	8
Relief	0	1	2	3	4	5	6	7	8
Sadness	0	1	2	3	4	5	6	7	8
Surprise	0	1	2	3	4	5	6	7	8
Tension	0	1	2	3	4	5	6	7	8

Last Minutes with Oden (2009) Directed by Eliot Rausch

Time	**Scene 2**
00:02:31 - 00:02:46	In the car, the dog owners friend is saying goodbye to the dog

Amusement	0	1	2	3	4	5	6	7	8
Anger	0	1	2	3	4	5	6	7	8
Arousal	0	1	2	3	4	5	6	7	8
Confusion	0	1	2	3	4	5	6	7	8
Contempt	0	1	2	3	4	5	6	7	8
Contentment	0	1	2	3	4	5	6	7	8
Disgust	0	1	2	3	4	5	6	7	8
Embarrassment	0	1	2	3	4	5	6	7	8
Fear	0	1	2	3	4	5	6	7	8
Happiness	0	1	2	3	4	5	6	7	8
Interest	0	1	2	3	4	5	6	7	8
Pain	0	1	2	3	4	5	6	7	8
Relief	0	1	2	3	4	5	6	7	8
Sadness	0	1	2	3	4	5	6	7	8
Surprise	0	1	2	3	4	5	6	7	8
Tension	0	1	2	3	4	5	6	7	8

Last Minutes with Oden (2009) Directed by Eliot Rausch

Time	**Scene 3**
00:03:55 - 00:04:22	At the vet the woman is cradling the dog, dog owner kisses the dog before he gets up to leave

Amusement	0	1	2	3	4	5	6	7	8
Anger	0	1	2	3	4	5	6	7	8
Arousal	0	1	2	3	4	5	6	7	8
Confusion	0	1	2	3	4	5	6	7	8
Contempt	0	1	2	3	4	5	6	7	8
Contentment	0	1	2	3	4	5	6	7	8
Disgust	0	1	2	3	4	5	6	7	8
Embarrassment	0	1	2	3	4	5	6	7	8
Fear	0	1	2	3	4	5	6	7	8
Happiness	0	1	2	3	4	5	6	7	8
Interest	0	1	2	3	4	5	6	7	8
Pain	0	1	2	3	4	5	6	7	8
Relief	0	1	2	3	4	5	6	7	8
Sadness	0	1	2	3	4	5	6	7	8
Surprise	0	1	2	3	4	5	6	7	8
Tension	0	1	2	3	4	5	6	7	8

Have you seen this short film before? Yes / No / Can't Remember (circle one)

Lights Out (2013) Directed by David F. Sandberg

Time	**Scene 1**								
00:00:50 - 00:00:55	At one end of the hallway, the woman turns the light off and the silhouette is no longer there, she jumps up.								
Amusement	0	1	2	3	4	5	6	7	8
Anger	0	1	2	3	4	5	6	7	8
Arousal	0	1	2	3	4	5	6	7	8
Confusion	0	1	2	3	4	5	6	7	8
Contempt	0	1	2	3	4	5	6	7	8
Contentment	0	1	2	3	4	5	6	7	8
Disgust	0	1	2	3	4	5	6	7	8
Embarrassment	0	1	2	3	4	5	6	7	8
Fear	0	1	2	3	4	5	6	7	8
Happiness	0	1	2	3	4	5	6	7	8
Interest	0	1	2	3	4	5	6	7	8
Pain	0	1	2	3	4	5	6	7	8
Relief	0	1	2	3	4	5	6	7	8
Sadness	0	1	2	3	4	5	6	7	8
Surprise	0	1	2	3	4	5	6	7	8
Tension	0	1	2	3	4	5	6	7	8

Lights Out (2013) Directed by David F. Sandberg

Time	**Scene 2**								
00:01:35 - 00:1:55	The woman is in bed, she hears footsteps and pulls the blanket over her head								
Amusement	0	1	2	3	4	5	6	7	8
Anger	0	1	2	3	4	5	6	7	8
Arousal	0	1	2	3	4	5	6	7	8
Confusion	0	1	2	3	4	5	6	7	8
Contempt	0	1	2	3	4	5	6	7	8
Contentment	0	1	2	3	4	5	6	7	8
Disgust	0	1	2	3	4	5	6	7	8
Embarrassment	0	1	2	3	4	5	6	7	8
Fear	0	1	2	3	4	5	6	7	8
Happiness	0	1	2	3	4	5	6	7	8
Interest	0	1	2	3	4	5	6	7	8
Pain	0	1	2	3	4	5	6	7	8
Relief	0	1	2	3	4	5	6	7	8
Sadness	0	1	2	3	4	5	6	7	8
Surprise	0	1	2	3	4	5	6	7	8
Tension	0	1	2	3	4	5	6	7	8

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Time	**Scene 3**
00:02:35 - 00:02:47	The woman takes the blanket covers off her head to look around, when she turns towards the lamp, she sees a monster

Amusement	0	1	2	3	4	5	6	7	8
Anger	0	1	2	3	4	5	6	7	8
Arousal	0	1	2	3	4	5	6	7	8
Confusion	0	1	2	3	4	5	6	7	8
Contempt	0	1	2	3	4	5	6	7	8
Contentment	0	1	2	3	4	5	6	7	8
Disgust	0	1	2	3	4	5	6	7	8
Embarrassment	0	1	2	3	4	5	6	7	8
Fear	0	1	2	3	4	5	6	7	8
Happiness	0	1	2	3	4	5	6	7	8
Interest	0	1	2	3	4	5	6	7	8
Pain	0	1	2	3	4	5	6	7	8
Relief	0	1	2	3	4	5	6	7	8
Sadness	0	1	2	3	4	5	6	7	8
Surprise	0	1	2	3	4	5	6	7	8
Tension	0	1	2	3	4	5	6	7	8

Have you seen this short film before? Yes / No / Can’t Remember (circle one)

Vector Magnitudes – Frontal facial views

Amusement - Highest Areas

Amusement- Frontal- Highest Area of Average Vector Magnitude N=96				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	0	0	0
2	30° - 60°	9	9	2
3	60° - 90°	60	63	16
4	90° - 120°	43	45	11
5	120° - 150°	2	2	1
6	150° - 180°	10	10	3
7	180° - 210°	23	24	6
8	210° - 240°	28	29	7
9	240° - 270°	86	90	22
10	270° - 300°	81	84	21
11	300° - 330°	22	23	6
12	330° - 360°	20	21	5
TOTAL		384	400	100

Sadness- Highest Areas

Sadness- Frontal- Highest Area of Average Vector Magnitude N=44				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	0	0	0
2	30° - 60°	7	16	4
3	60° - 90°	18	41	10
4	90° - 120°	21	48	12
5	120° - 150°	3	7	2
6	150° - 180°	6	14	3
7	180° - 210°	19	43	11
8	210° - 240°	19	43	11
9	240° - 270°	37	84	21
10	270° - 300°	33	75	19
11	300° - 330°	6	14	3
12	330° - 360°	7	16	4
TOTAL		176	400	100

Fear- Highest Areas

Fear- Frontal- Highest Area of Average Vector Magnitude N=44				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	1	2	1
2	30° - 60°	11	25	6
3	60° - 90°	37	84	21
4	90° - 120°	29	66	16
5	90° - 120°	3	7	2
6	150° - 180°	3	7	2
7	180° - 210°	4	9	2
8	210° - 240°	6	14	3
9	240° - 270°	33	75	19
10	270° - 300°	34	77	19
11	300° - 330°	7	16	4
12	330° - 360°	8	18	5
TOTAL		176	400	100

Amusement- Intermediate Areas

Amusement- Frontal- Intermediate Area of Average Vector Magnitude N=96				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	11	11	3
2	30° - 60°	35	36	9
3	60° - 90°	30	31	8
4	90° - 120°	46	48	12
5	120° - 150°	24	25	6
6	150° - 180°	39	41	10
7	180° - 210°	45	47	12
8	210° - 240°	39	41	10
9	240° - 270°	8	8	2
10	270° - 300°	14	15	4
11	300° - 330°	44	46	11
12	330° - 360°	49	51	13
TOTAL		384	400	100

Sadness- Intermediate Areas

Sadness- Frontal- Intermediate Area of Average Vector Magnitude N=44				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	10	23	6
2	30° - 60°	9	20	5
3	60° - 90°	21	48	12
4	90° - 120°	19	43	11
5	120° - 150°	14	32	8
6	150° - 180°	21	48	12
7	180° - 210°	19	43	11
8	210° - 240°	15	34	9
9	240° - 270°	3	7	2
10	270° - 300°	5	11	3
11	300° - 330°	20	45	11
12	330° - 360°	20	45	11
TOTAL		176	400	100

Fear- Intermediate Areas

Fear- Frontal- Intermediate Area of Average Vector Magnitude N=44				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	11	25	6
2	30° - 60°	15	34	9
3	60° - 90°	6	14	3
4	60° - 90°	15	34	9
5	120° - 150°	19	43	11
6	150° - 180°	20	45	11
7	180° - 210°	24	55	14
8	210° - 240°	18	41	10
9	240° - 270°	6	14	3
10	270° - 300°	7	16	4
11	300° - 330°	15	34	9
12	330° - 360°	20	45	11
TOTAL		176	400	100

Amusement- Lowest Areas

Amusement- Frontal- Lowest Area of Average Vector Magnitude N=96				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	85	89	22
2	30° - 60°	52	54	14
3	60° - 90°	6	6	2
4	90° - 120°	7	7	2
5	120° - 150°	70	73	18
6	150° - 180°	47	49	12
7	180° - 210°	28	29	7
8	210° - 240°	29	30	8
9	240° - 270°	2	2	1
10	270° - 300°	1	1	0
11	300° - 330°	30	31	8
12	330° - 360°	27	28	7
TOTAL		384	400	100

Sadness- Lowest Areas

Sadness- Frontal- Lowest Area of Average Vector Magnitude N=96				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	34	77	19
2	30° - 60°	28	64	16
3	60° - 90°	5	11	3
4	90° - 120°	4	9	2
5	120° - 150°	27	61	15
6	150° - 180°	17	39	10
7	180° - 210°	6	14	3
8	210° - 240°	10	23	6
9	240° - 270°	4	9	2
10	270° - 300°	6	14	3
11	300° - 330°	18	41	10
12	330° - 360°	17	39	10
TOTAL		176	400	100

Fear- Lowest Areas

Fear- Frontal- Lowest Area of Average Vector Magnitude N=44				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	32	73	18
2	30° - 60°	18	41	10
3	60° - 90°	1	2	1
4	60° - 90°	0	0	0
5	120° - 150°	22	50	13
6	150° - 180°	21	48	12
7	180° - 210°	16	36	9
8	210° - 240°	20	45	11
9	240° - 270°	5	11	3
10	270° - 300°	3	7	2
11	300° - 330°	22	50	13
12	330° - 360°	16	36	9
TOTAL		176	400	100

Vector magnitudes – Left profile facial views

Amusement- Highest Areas

Amusement- Profile Left- Highest Area of Average Vector Magnitude N=96				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	0	0	0
2	30° - 60°	15	16	4
3	60° - 90°	51	53	13
4	90° - 120°	55	57	14
5	90° - 120°	2	2	1
6	150° - 180°	6	6	2
7	180° - 210°	27	28	7
8	210° - 240°	35	36	9
9	240° - 270°	83	86	22
10	270° - 300°	85	89	22
11	300° - 330°	14	15	4
12	330° - 360°	11	11	3
TOTAL		384	400	100

Sadness- Highest Areas

Sadness- Profile Left- Highest Area of Average Vector Magnitude N=44				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	0	0	0
2	30° - 60°	5	11	3
3	60° - 90°	29	66	16
4	90° - 120°	23	52	13
5	90° - 120°	4	9	2
6	150° - 180°	3	7	2
7	180° - 210°	10	23	6
8	210° - 240°	13	30	7
9	240° - 270°	37	84	21
10	270° - 300°	40	91	23
11	300° - 330°	3	7	2
12	330° - 360°	9	20	5
TOTAL		176	400	100

Fear- Highest Areas

Fear- Profile Left- Highest Area of Average Vector Magnitude N=44				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	1	2	1
2	30° - 60°	11	25	6
3	60° - 90°	33	75	19
4	90° - 120°	24	55	14
5	90° - 120°	5	11	3
6	150° - 180°	8	18	5
7	180° - 210°	8	18	5
8	210° - 240°	11	25	6
9	240° - 270°	36	82	20
10	270° - 300°	31	70	18
11	300° - 330°	3	7	2
12	330° - 360°	5	11	3
TOTAL		176	400	100

Amusement- Intermediate Areas

Amusement- Profile Left- Intermediate Area of Average Vector Magnitude N=96				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	9	9	2
2	30° - 60°	30	31	8
3	60° - 90°	38	40	10
4	60° - 90°	33	34	9
5	90° - 120°	30	31	8
6	150° - 180°	46	48	12
7	180° - 210°	46	48	12
8	210° - 240°	44	46	11
9	240° - 270°	12	13	3
10	270° - 300°	7	7	2
11	300° - 330°	47	49	12
12	330° - 360°	42	44	11
TOTAL		384	400	100

Sadness- Intermediate Areas

Sadness- Profile Left- Intermediate Area of Average Vector Magnitude N=44				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	5	11	3
2	30° - 60°	18	41	10
3	60° - 90°	10	23	6
4	90° - 120°	19	43	11
5	90° - 120°	14	32	8
6	150° - 180°	21	48	12
7	180° - 210°	22	50	13
8	210° - 240°	23	52	13
9	240° - 270°	7	16	4
10	270° - 300°	3	7	2
11	300° - 330°	19	43	11
12	330° - 360°	15	34	9
TOTAL		176	400	100

Fear Intermediate Areas

Fear- Profile Left- Intermediate Area of Average Vector Magnitude Magnitude N=44				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	6	14	3
2	30° - 60°	18	41	10
3	60° - 90°	8	18	5
4	90° - 120°	19	43	11
5	90° - 120°	16	36	9
6	150° - 180°	12	27	7
7	180° - 210°	16	36	9
8	210° - 240°	23	52	13
9	240° - 270°	8	18	5
10	270° - 300°	10	23	6
11	300° - 330°	19	43	11
12	330° - 360°	21	48	12
TOTAL		176	400	100

Amusement-Lowest Areas

Amusement- Profile Left- Lowest Area of Average Vector Magnitude N=96				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	87	91	23
2	30° - 60°	51	53	13
3	60° - 90°	7	7	2
4	60° - 90°	8	8	2
5	120° - 150°	64	67	17
6	150° - 180°	44	46	11
7	180° - 210°	23	24	6
8	210° - 240°	17	18	4
9	240° - 270°	1	1	0
10	270° - 300°	4	4	1
11	300° - 330°	35	36	9
12	330° - 360°	43	45	11
TOTAL		384	400	100

Sadness- Lowest Areas

Sadness- Profile Left- Lowest Area of Average Vector Magnitude N=44				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	39	89	22
2	30° - 60°	21	48	12
3	60° - 90°	5	11	3
4	60° - 90°	2	5	1
5	120° - 150°	26	59	15
6	150° - 180°	20	45	11
7	180° - 210°	12	27	7
8	210° - 240°	8	18	5
9	240° - 270°	0	0	0
10	270° - 300°	1	2	1
11	300° - 330°	22	50	13
12	330° - 360°	20	45	11
TOTAL		176	400	100

Fear- Lowest Areas

Fear- Profile Left- Lowest Area of Average Vector Magnitude Magnitude N=44				
Sector	**Angle**	**Total**	**Subjects (%)**	**Frequency (%)**
1	**0° - 30°**	37	84	21
2	**30° - 60°**	15	34	9
3	**60° - 90°**	3	7	2
4	**60° - 90°**	1	2	1
5	**120° - 150°**	23	52	13
6	**150° - 180°**	24	55	14
7	**180° - 210°**	20	45	11
8	**210° - 240°**	10	23	6
9	**240° - 270°**	0	0	0
10	**270° - 300°**	3	7	2
11	**300° - 330°**	22	50	13
12	**330° - 360°**	18	41	10
TOTAL		176	400	100

Vector Magnitudes – Right profile facial views

Amusement- Highest Areas

Amusement- Profile Right- Highest Area of Average Vector Magnitude N=96				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	0	0	0
2	30° - 60°	10	10	3
3	60° - 90°	53	55	14
4	90° - 120°	55	57	14
5	90° - 120°	14	15	4
6	150° - 180°	15	16	4
7	180° - 210°	12	13	3
8	210° - 240°	19	20	5
9	240° - 270°	76	79	20
10	270° - 300°	81	84	21
11	300° - 330°	26	27	7
12	330° - 360°	23	24	6
TOTAL		384	400	100

Sadness- Highest Areas

Sadness- Profile Right- Highest Area of Average Vector Magnitude N=44				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	1	2	1
2	30° - 60°	6	14	3
3	60° - 90°	32	73	18
4	90° - 120°	27	61	15
5	90° - 120°	2	5	1
6	150° - 180°	4	9	2
7	180° - 210°	3	7	2
8	210° - 240°	3	7	2
9	240° - 270°	35	80	20
10	270° - 300°	37	84	21
11	300° - 330°	13	30	7
12	330° - 360°	13	30	7
TOTAL		176	400	100

Fear- Highest Areas

Fear- Profile Right- Highest Area of Average Vector Magnitude N=44				
Sector	**Angle**	**Total**	**Subjects (%)**	**Frequency (%)**
1	**0° - 30°**	3	7	2
2	**30° - 60°**	11	25	6
3	**60° - 90°**	34	77	19
4	**90° - 120°**	29	66	16
5	**90° - 120°**	5	11	3
6	**150° - 180°**	7	16	4
7	**180° - 210°**	3	7	2
8	**210° - 240°**	5	11	3
9	**240° - 270°**	30	68	17
10	**270° - 300°**	30	68	17
11	**300° - 330°**	5	11	3
12	**330° - 360°**	14	32	8
TOTAL		176	400	100

Amusement- Intermediate Areas

Amusement- Profile Right- Intermediate Area of Average Vector Magnitude N=96				
Sector	**Angle**	**Total**	**Subjects (%)**	**Frequency (%)**
1	**0° - 30°**	9	9	2
2	**30° - 60°**	23	24	6
3	**60° - 90°**	38	40	10
4	**60° - 90°**	37	39	10
5	**90° - 120°**	31	32	8
6	**150° - 180°**	41	43	11
7	**180° - 210°**	47	49	12
8	**210° - 240°**	44	46	11
9	**240° - 270°**	19	20	5
10	**270° - 300°**	13	14	3
11	**300° - 330°**	38	40	10
12	**330° - 360°**	44	46	11
TOTAL		384	400	100

Sadness- Intermediate Areas

Sadness- Profile Right- Intermediate Area of Average Vector Magnitude N=44				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	6	14	3
2	30° - 60°	19	43	11
3	60° - 90°	12	27	7
4	60° - 90°	16	37	9
5	90° - 120°	16	37	9
6	150° - 180°	18	41	10
7	180° - 210°	17	39	10
8	210° - 240°	16	37	9
9	240° - 270°	5	11	3
10	270° - 300°	7	16	4
11	300° - 330°	24	55	14
12	330° - 360°	19	43	11
TOTAL		175	400	100

Fear- Intermediate Areas

Fear- Profile Right- Intermediate Area of Average Vector Magnitude N=44				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	7	16	4
2	30° - 60°	13	30	7
3	60° - 90°	9	20	5
4	60° - 90°	14	32	8
5	90° - 120°	16	36	9
6	150° - 180°	19	43	11
7	180° - 210°	18	41	10
8	210° - 240°	18	41	10
9	240° - 270°	14	32	8
10	270° - 300°	14	32	8
11	300° - 330°	19	43	11
12	330° - 360°	15	34	9
TOTAL		176	400	100

Amusement- Lowest Areas

Amusement- Profile Right- Lowest Area of Average Vector Magnitude N=96				
Sector	**Angle**	**Total**	**Subjects (%)**	**Frequency (%)**
1	**0° - 30°**	87	91	23
2	**30° - 60°**	63	66	16
3	**60° - 90°**	5	5	1
4	**60° - 90°**	4	4	1
5	**120° - 150°**	51	53	13
6	**150° - 180°**	40	42	10
7	**180° - 210°**	37	39	10
8	**210° - 240°**	33	34	9
9	**240° - 270°**	1	1	0
10	**270° - 300°**	2	2	1
11	**300° - 330°**	32	33	8
12	**330° - 360°**	29	30	8
TOTAL		384	400	100

Sadness- Lowest Areas

Sadness- Profile Right- Lowest Area of Average Vector Magnitude N=44				
Sector	**Angle**	**Total**	**Subjects (%)**	**Frequency (%)**
1	**0° - 30°**	37	84	21
2	**30° - 60°**	19	43	11
3	**60° - 90°**	0	0	0
4	**60° - 90°**	1	2	1
5	**120° - 150°**	26	59	15
6	**150° - 180°**	22	50	12
7	**180° - 210°**	24	54	14
8	**210° - 240°**	25	56	14
9	**240° - 270°**	4	9	2
10	**270° - 300°**	0	0	0
11	**300° - 330°**	7	16	4
12	**330° - 360°**	12	27	7
TOTAL		177	400	100

Fear- Lowest Areas

Fear- Profile Right- Lowest Area of Average Vector Magnitude N=44				
Sector	Angle	Total	Subjects (%)	Frequency (%)
1	0° - 30°	34	77	19
2	30° - 60°	20	45	11
3	60° - 90°	1	2	1
4	60° - 90°	1	2	1
5	120° - 150°	23	52	13
6	150° - 180°	18	41	10
7	180° - 210°	23	52	13
8	210° - 240°	21	48	12
9	240° - 270°	0	0	0
10	270° - 300°	0	0	0
11	300° - 330°	20	45	11
12	330° - 360°	15	34	9
TOTAL		176	400	100