Wavelet based Multimedia Data Compression Techniques

Thesis by

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Dedication

To my father, my heart broke when you left during my studies. I will never forget your love and support, and your memories continue to regulate my life. I am dedicating this thesis (our dream) to you. Thank you so much.

To my mother, your encouragement and being by my side had the greatest role in my efforts to complete my studies. Please accept my good feelings, respect and appreciation for you. I love you.

To my husband (my second half), Muneer and my kids Fadi and Faten, I have derived from you all a strong source of love, affection and positive energy. I also dedicate this thesis to you. Thanks for your patience throughout the years completing my thesis.

Arabic Dedication

الحمدلله مبلغ الرضى .. مبلغ الكمال .. مبلغ الامتنان .. الحمدلله احساس يملأ الكون سعاده

الحمدلله حياة فوق الحياة وأمل جديد يفتح لي أبواب السماء .. الحمدلله قلب ينبض كقلب طفل وليد يقبل على أول مداركه في الحياة

هاهي الأيام والسنين تمضي لتحمل في طياتها ثمرة نجاحي وانجازي في مسيرة دراستي ... ليتحقق حلم طالما انتظرته

من هنا أود أن اشكرمشرفي على كل مابذله معي من بداية مرحلة الدكتوراه الى هذه اللحظه

ومن ثم أود أن أشكر زوجي الغالي منيروأولادي فادي وفاتن على صبرهم فلقد كانوا الداعم الأول والأخيرلي بايجابيتهم دائما

ومن ثم أشكرمن كانت تحفني بدعائها صاحبة القلب الطيب أمي الغاليه مريم ..
وأشكرأخواني وأخواتي على وجودهم في حياتي فهم منبع سعادتي في حياتي

ومن ثم أشكروالدي الذي طال انتظاره ولم يستطع حضورهذه اللحظة رحمة الله عليه فهأنا أبي حققت حلمك

عائلتي وصديقاتي هم سبب نجاحي أشكركم فرداً فرداً فلولا الله ثم وجودكم في حياتي لما توصلت لهذا الانجاز

Originality Statement

I, Hanadi Hakami declare that this thesis, is submitted in fulfilment of the requirements for the award of PhD, in the Faculty of Engineering and Information Technology, at the University of Technology Sydney. This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of the requirements for a degree at any other academic institution except as fully acknowledged within the text. This research is supported by the Australian Government Research Training Program.

Production Note:

Signature: Signature removed prior to publication.

Acknowledgments

After an intense period of academic studies, today is the day; writing these simple words to express my thanks is the finishing touch on my dissertation.

I have found the research process to be a very valuable learning experience, not only in regards to my research field, but on a personal level, also. Completing this thesis has had a significant impact on me and I would like to take the opportunity to acknowledge all the people who have supported me throughout the process.

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I am profoundly grateful to my mother, husband, sisters and brothers for their sincere support and love during this research process. Also, my sincere thanks to all of my friends.

Lastly, I would like to thank my dear government for the scholarship which provided me with this opportunity to complete my doctoral studies.

Terms and Definitions

Lossy Compression Technique: Using this technique the original file cannot be created according to its uncompressed version.

Lossless Compression Technique: Using this technique the input is obtained in its actual shape without any loss of data, as after decoding the data can be restored in its exact form like the original.

Compress Image: It is reducing the image size to the acceptable level without degrading the quality of this image.

Compression Rate: It is the representation of data size to quantify the reduction outputted by a compression-based algorithm.

Compression Quality: It is a measure of an image compression process which compares between data sizes and structural sameness with the original and compressed images.

Wavelet Transforms: Are mathematical tools for presenting images signals when signal frequency varies over time, remove noise and compressed images.

Human Visual System: The model of HVS is a mathematical representation of the way humans perceive the world. Also, is about dealing with processes of a psychological and biological nature that are yet to be understood fully. Commonly, one thinks of "taking advantage" of the HVS technique to ensure desirable effects.

Multimedia: Field where computer-controllanle integration of graphics, drawings, text, video and other forms of media of the which the information can be representable, storable, transmittable and digitally processed.

Multi-Resolution: The design methodology of relevant and practical discrete wavelet transforms (DWT). Multi-resolution is considered as part of wavelet studies. Wavelets are described best as mathematical objects (i.e. functions or signals) at resolutions with differing levels.

Most Significant Bits: Refers to the bit of greatest value in a multi-bit binary number. The bit to the utmost left is the most significant. Binary numbers are mostly used in computing and its related domains. As such, the bit which is most significant is important, particularly in relation to the binary number transmission.

Critical Section: Code segmentation accessesing variables that are shared and must be executable atomically. Therefore, in a cooperating process group, at a given time point, a single process must execute its section critically.

Image Contrast: Refers to the contrast in luminousity/colour, rendering the object (or depiction in display) unique. When visually perceiving the surrounding environment, contrast emerges from the variations in brightness and colour of the object and in relation to different objects which may also be in view.

Nomenclature

2D	Two Dimensional
3D	Three Dimensional
AHE	Adaptive Histogram Equalisation
BHE	Bi-Histogram Equalisation
BMP	Bitmap
BPP	Bits Per Pixel
CDF	Cumulative Density Function
CS	Compressive Sensing
CSF	Contrast Sensitivity Function
CSF	Contrast Sensitivity Function
DCT	Discrete Cosine Transform
DCT	Discrete Cosine Transform
DFT	Discrete Fourier transform
DWT	Discrete Wavelet Transform
DWT	Discrete Wavelet Transform
EZW	Embedded Zero-tree Wavelet
GPS	Global Positioning Systems
HDR	High Dynamic Range of Images
HE	Histogram Equalization
HE	Histogram Equalization
HH	High-High Frequency Domain

HL	High-Low Frequency Domain
HPF	High Pass Filter
HS-SPIHT	Highly Scalable Set Partitioning in Hierachical Trees
HVS	Human Visual System
ICT	Information and Communication Technology
IFS	Iterated Function System
IMU	Inertial Measurement Unit
JND	Just Noticeable Difference
JPEG	Joint Photographic Expert Group
JPEG 2000	Joint Photographic Expert Group 2000
JPG	Joint Photographic Graphics
LDIS	List of Delayed Insignificant Sets
LH	Low-High Frequency Domain
LiDAR	Airborne Light Detection and Ranging
LIP	List of Irrelevant Pixels
LIS	List of Irrelevant Sets
LL	Low-Low Frequency Domain
LMOs	Large Multimedia Objectives
LPF	Low Pass Filter
LPS	Less Probable Symbol
LSP	List of Significant Pixels
LZW	Lempel-Ziv-Welch Compression Technique
MOS	Mean Opinion Score
MPEG	Moving Picture Experts Group
MPS	More Probable Symbol

MSB	Most Significant Byte
MSE	Mean Square Error
NVF	Noise Visibility Function
PNG	Portable Network Graphics
PQS	Picture Quality Scale
PSNR	Peak Signal to Noise Ratio
RLE	Run Length Encoding
SOTs	Spatial Orientation Trees
SPIHT	Set Partitioning in Hierachical Trees
SQE	Subjective Quality Evaluation
SSIM	Structural Similarity Index
SVM	Support Vector Machine
TIFF	Tagged Image File Format
UQI	Universal Image Quality Index
VM	Verification Model
VQ	Vector Quantisation
WCTQ	Wavelet Coded Trellis Quantization
WT	Wavelet Transform

Contents

List of Figures

List of Tables

Abstract

The field of Multimedia computing has become major research into data compression. Multimedia computing is essentially the integration of audio, video (high or low definition), graphics, photography, text and software; has led to the development of various handling applications employing data compression. Frequently, a large amount of data created by these handlers has to be stored and often transferred from device/s to device/s over the Internet and various other transmission media. Accordingly, the often "bigger" data requires wider bandwidth, and longer processing and storage times.

This research focused on multiple data compression techniques, depending on the expected quality of "de-compressed" data and in-image processing, in particular. A large amount of research involved development of image compression coding technologies and standards. The coding technologies applied image compression technologies employing: the Human Visual System (HVS) model including auditory characteristics, Continuous Wavelet Transform (CWT), Image Enhancement and Fractal theory. Data compression is most widely used in spreadsheet applications, backup utilities, graphics and database management system.

Several reasons were investigated as to why multimedia signals require data to be compressed and as stated previously, the principal reasons include storage that needs to be managed by the quality of the data. Suitable use of Evolutionary Algorithm and effective use of the wavelets transform based Human Visual System in data compression is investigated in this thesis. Firstly, two approaches of data compression techniques are developed with the use of the aforementioned features. The first method aims to overcome the issues with the quality of the compressed images for cases when the original file cannot be recreated according to its uncompressed version while reducing bits required to transmit and store an image file. The second approach proposes a dedicated compression technique in which the input is obtained in its actual shape without loss of data, as after decoding the data can be restored in its original and exact form. These approaches were enhanced by developing the Quality Enhancement Techniques for effective imperceptibility measurement of compressed data. To assess the utility and viability of techniques proposed, they all have been empirically validated. This research considered data compression as a solution in the retrieval, store and transmission of data that ensures a balance between compression times, quality of compression and compression rate that utilizes the HVS system model.

1 Introduction to Data Compression Techniques

1.1 Overview

The continuous growth of technology for modernized communications means the demand for transmitting and storing imagery is at a rapid increase. Advancements in computerized technology for storage of data and digitized processing has led to the implementation of advancements in techniques of data compression to aid the efficient transmitting and to store of image data. Image process methodologies are getting advanced, along with the trend of automating to a high degree of sophistication. The aim of image processable techniques applicable to handle large amounts of data creates a problem. Data transmission bandwidth has always been problematic, particularly for large volume data. In the past, a data item was usually limited to 8 bit bytes. But with the increased use of multimedia technologies simple data transmission, storage or even management could result in handling huge amounts of data per multimedia item or sequence of items (Shajeemohan & Govindan (2005)).

Multimedia data often considers primary types of media including:

- Text,
- Images,
- Graphical objects,
- Sketches,
- Illustrations,
- Animations,
- Audio,
- Video, and
- Other pixel rich data items (Gandomi & Haider (2015)).

Multimedia data items are often organized into persistent collections that include different formats, usually designated by file extensions, with emphasis on original data compression techniques including:

- wav: lossless, uncompressed, broadcast CD quality music files;

- mp3: means of compressing audio (usually sound) into a smaller package to assist data transmission and storage;
- mp4: similar to mp3 but not exclusively audio, also includes video, still imagery, text and often preferable to the "digital multimedia container";
- mpg: a file extension for MPEG 1 and/or 2 which is an ISO standardization for encoding/compressing audio and video data;
- wmv: a video collection based on Microsoft's video codec, coding formats – similar to Advanced System Formats (ASF);
- avi: an interleaving format of video and audio.

Hence, a large volume of data is created when imagery is digitized, thus feature-rich persistent imagery requires larger storage space; uses up greater time for processing and transmitting (Kaur et al. (2015)). Big data is a terminology describing significant data volume – in a structured and/or unstructured format. This data is very complex and in a high volume so it becomes very difficult for traditional data processing applications to handle (Bonde, P. and Barahate (2017)).

As an overall outcome, big data Compressibility is an advancing technology to reduce redundancy in representability of data, bearing the final goal post is to reduce data store use and costings as depicted in Figure 1.1, which shows the original data before and after reducing the data volume using compression processes (Faust (1979)). The primary being of compression is to retain the quality of the imagery, whilst lowering the amount of "Data" necessary to transmit and store as a file. Compression of images occurs by taking advantage of redundancies in perception and space within the data describing the image. Best compression includes only pertinent information required to successfully re-construct imagery with minimal loss in clarity.

- Perceptual redundancies refer to: A compression algorithm most efficient that is effectively not observable to the human eye is required for the representation of high-quality colour images, as there are limited resources of storage or bandwidth transmission. Exploiting perceptive redundancies typical in digitized imagery has been proven great in the enhancement of performance of digital image processing systems - especially in the realm of data compression (Chou, C.H. and Liu (2004)).
- Spatial redundancies refer to: A removal process that is performed through detecting edges and dividing the image into homogeneous regions. Also, exploiting spatial redundancy is how compression is performed (Bastani et al. (2010)).

The success of compressing multimedia considers balancing performance parameters advancing the ratio of compression, minimum time and increase compression quality. The compression measure ratio is one of the performance parameters, to ratios considering affectivity of both the original multimedia prior to compression and measuring data sizes afterwards; i.e. ratio before and after. The compressed image factors proving of perceptual and spatial redundancy by ensuring necessary data to a base, without unacceptable trading-off in visual quality (Uthayakumar et al. (2018)). Additionally, multimedia data is also time limited and needs in time must be satisfied. Supporting multimedia data compression, ratio, quality and time are traded off to maximize data compression quality and multimedia data ratio in real time.

Limits in bandwidth and typical storage mean much of the available modern applications require a compression technique for digital images. Various techniques deal with the data compression concern:

- Moving Picture Experts Group (MPEG) refers to a group of standards and file setups utilized in digital videos. MPEG is considered a particularly good choice because it supports streaming high quality video on multiple platforms such as the Internet.
- Joint Photographic Expert Group (JPEG) refer to a compression based standard (ISO/IEC 10918). It is a popular choice when aiming to encode and compress photographs.
- Discrete Wavelet Transform (DWT) is the term used for the signal represented via a linear mixture of mathematical functions used when compressing images and processing digital signals (Singh (1999)). The mathematical functions can be isolated in terms of frequency to wave number and time to spatial position. Compressed images utilizing wavelet technology are not as large as JPEG images and as a result the transmission and the downloading process is quicker. The use of DWT is common in the compression of images, signals and videos (Walker, J.S. and Nguyen (2001)).
- Discrete Cosine Transform (DCT) refers to the methodology for changing the signal to its basic frequency elements, commonly utilized to compress images (Watson (1994)).

The Wavelet Transform is acknowledged as a considerable and vital utility for representing signals as small waves. Wavelet theory posits that transformed wavelets are a type of time and frequency depiction for constant signals. Most DWTs utilize distinct time filters and are a function in accordance with the uncertainty principle embedded in the Fourier Analysis. There are three classes of wavelet transforms: discrete, continuous and multi-resolution which are discussed in detail within chapter 2 (Walker, J.S. and Nguyen (2001)).

A wavelet may be characterized as a continuous sine wave with specific bandwidth and curve. Wavelets contribute to a decrease in the length of data to a specific frequency and are utilized in data compression to deconstruct signals at different resolutions, referred to as multi-resolution (Staadt, O.G., Gross, M.H. and Weber (1997)). Identifying the wavelength filter resulting in the lowest amount of non-zero coefficients and is the best technique to achieve good compression outcomes. This makes it possible to utilize the **Human Visual System** (HVS); that is, a mathematical representation of the way humans perceive the world (more explanation within chapter 3).

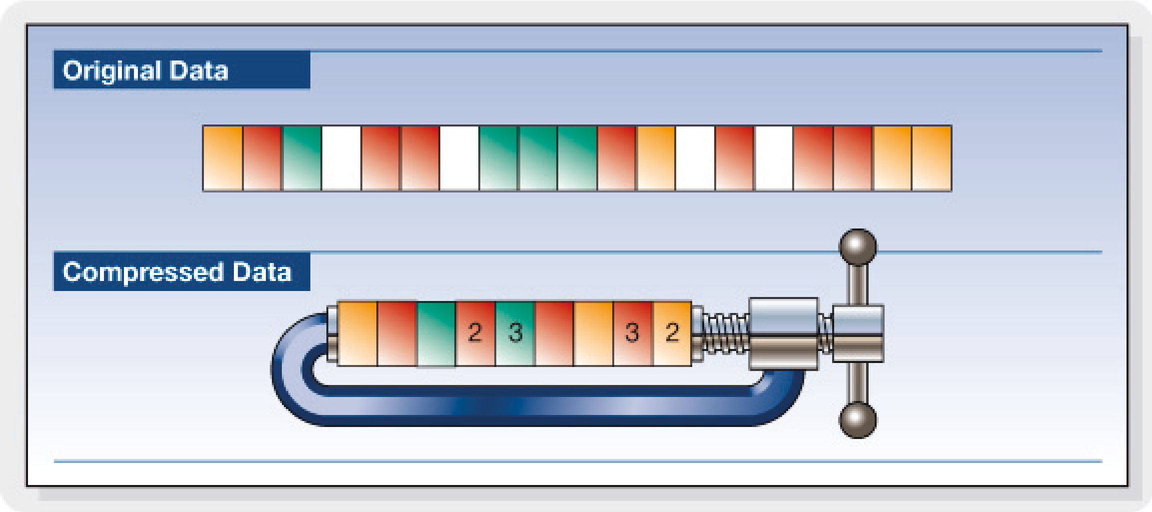


Figure 1.1: Data compression (Faust (1979))

1.2 Research Problem

Advances in **multimedia** technology mean the request for transmitting and storing multimedia has increased notably. Large data volumes require more storage space and time for processing and eventual transmission. Thus, Data Compression is one of these techniques to lower the redundancy, the total data size and solve time that is spent handling and storing data with a great degree of quality.

With wide spread digital artifacts, there is a high demand for multimedia compression. There are trade-offs in the quality of compression, time of compression and ratio of compression and these property types often conflict with each other. Therefore, the more data that is compressed, degradation accrues in the image that is compressed. So, it is critical to have effective techniques in compression that ensure a high ratio of compression ratio without affecting the overall quality.

In the context of IoT, Cloud Computing has gained importance for today's world as the technology field goes beyond boundaries - a driver to connect users to their resources without physicality in a distributed system environment. Thus the potential benefits of data compression are to reduce the traffic in the cloud.

Therefore, effective techniques to reduce storage space in the cloud also reduces the uploading time.

1.3 Research Context

Compression technique plays a vital role in modern of Information and Communication Technology (ICT), specifically for multimedia, big data, cloud computing and domains where big data exist. This is not only in these domains, but in various system environments which deal with large data. Is not only saves on storage costs but also processing time, transmission time, visualization time and quality enhancement of the imagery being compressed.

Thus, effective compression of imaging solutions is reaching a level of criticality with the rise in web and multimedia driven applications. Developing compression techniques with high efficiency is a design task for modern telecommunication systems and multimedia resources. Due to the increased size of Multimedia which comes from various heterogeneous sources - the storing, maintaining, processing and transferring of Big Data is becoming a considerable duty. Usually, the data has redundant and irrelevant information which can be eliminated to lower the size of files in a manageable way. Achieving this is done through various techniques known as techniques of compression. The approaches can be utilized for video, audio, images, text and digital information. The data compression techniques not only increase the transfer time but also reduce the processing time without degrading compressed information's quality.

The concept of compression is a boon for optimizing storage space in cloud computing. Any organization that is oriented to data security and having the constraint of storage space adopt the compression techniques. The compression mechanism is to cut storage costs. Mostly, the disk data storage has some redundancy statistically which can be compacted. Compressing such data reduces the amount of storage needed to be at least a third of total space. Data owners and data readers are seeking mechanisms which can take advantage of lossless and transparent storage technologies using compression to manage storage costs. Compressing large data leads to optimum utilization of cloud storage as large-sized data has grown exponentially over time.

1.4 Research Motivation

This section defines the motivation behind this research study and explains the basic purpose of imaging compressing, in such a way to present imagery with the minimum data as possible. The aggregate bit size required to transmit or store the digital images and the advanced video sources can be large. Primarily this number is more than the bandwidth of the transmission sources that is intended, the capacity limit of the storage content, making it difficult to engage in transferring digital images. Because most of the visual videos and images contain a lot of visual materializes and statistical redundancy, data compression or source coding techniques can apply to the data to diminish the quantity of the data, making extensive utilization of the digital imagery practical. Low cost has been associated with high quality of compressed digital images leading to the spread of high-quality multimedia. As a consideration, modern advancements in cameras and smartphones means that images have High Dynamic Range (HDR) typically included. Even though HDR images are of high-quality, it is noted that large storage media is required. The author's research is motivated by maintaining the imperceptibility or quality of HDR while diminishing the necessary storage space.

To use the data compression technique, there are two major reasons:

1. A large amount of data must be stored (persistent).
2. Transmitted through limited (bandwidth) channels.

Therefore, the compression application leads to reducing the massive amount of data in the disk space used and the required bandwidth. Images, audio, video and textual sources are examples of digitized objects that must be stored or transmitted. The usage of data compression technique doesn't only solve the problem of large data volumes but also to reduces the size of big data handling and storage, processing time and telemetry capability. There is a limitation for every compression algorithm in terms of efficiency which is using many different performance parameters. For this reason, a better compression technique efficiency that implies higher performance parameters and is less time-consuming. More details will be informed in Chapter 2.

There is a need to use data compression techniques to improve highly efficient service models for businesses and IT infrastructure. One way to provide this is to apply the HVS for this data compression to producing new dimensional multimedia with high-quality performance. The following points will explain the motivation of data compression:

1. Efficiency of Multimedia Data Compression
2. Evaluation of Multimedia Data Compression
3. Multimedia Data Compression Storage in Cloud
4. 2D versus 3D Images

1.4.1 Efficiency of Multimedia Data Compression

It has been observed by user that the processes of coding, storage and transmission of digital images can lead to image distortion. It is vital to have optimal compression of data to maintain the best quality image. A significant portion of current compression approaches concentrate on:

- Reducing the size of the images: Images are a visual representation which is composed by several information. To store each of these information take space. The image size is reduced to effectively perform image compression. The main types are essentially:

1. Lossless Technique
2. Lossy Technique

Lossless compression reduces the image size without the loss of a single pixel of the original image and Lossy results in some data loss.

- Faster delivery of the content: The algorithms for compression reduce data representation redundancy to reduce the storage needed for the data to be faster, and
- Faster writing and reading of persistent data: Data compression is an approach where data is represented with lesser data. Fewer data represents the original as it is represented with the help of larger data. With the assistance of less data, the size of data automatically decreases and leads to faster read and write times, uses less storage, and minimizes time downloading and uploading.

This research is primarily focused on reducing storage size while maintaining image quality. The success of any multimedia compression framework requires an astounding system that strikes a balance between upgrading the payload limit in capacity and the meantime, the need to send and receive valued information quickly and the imperceptibility of a specific compressed file.

1.4.2 Evaluation of Multimedia Data Compression

Thus, how to successfully assess the nature of resulting images turns into a significant problem as it typically shows the execution of the subsequent techniques of processing. To sensibly evaluate the quality of images, great imaging quality assessment measurements are requested and they can be utilized as the foundation to alter parameters of a preparing framework and upgrade algorithms as required. The execution of image pressure methods can also be substantially enhanced by embedding the properties of HVS in their pressure algorithms (Nadenau et al. (2000)).

1.4.3 Multimedia Data Compression Storage in Cloud

Due to fast, dynamic and competitive environments, Cloud Computing has become a significant tool around the globe as it has made a possible connection with users and resources without having a physical presence. Capacity in Cloud Computing is an essential part of the need for virtualized space to store the extensive information that has increased over the period of time. In any case, the pace of transferring and downloading has a limiting factor on the time of processing, and thus there is a drive to resolve the problem of extensive handling of information. Techniques of compression are a much dependable technique to decrease the space over the cloud as levels of popularity for digital information results in the improper utilization of cloud storage. For an extended discussion see in Chapter 6.

1.4.4 2D Versus 3D Images

All that discus previously related to 2D (Two Dimensional) but this research extends to 3D (Three Dimensional) which is back to 2D when using the 2D principle for filtering and data compression then it fails to be lossy or lossless, but lossy in an acceptable manner.

Two dimensional (2D) image may be a greyscale or colour image, although when using MATLAB, a 2D colour image is typically 3D as it comprises three 2D images representing each of the colour planes. Furthermore, a 2D shape by definition has two separate dimensions. This has implications for the work processes in that a 1D shape for instance can be moved backwards or forwards in a straight line only, given a line in 1D.

Three dimensional imaging is also referred to as stereoscopy. Stereoscopic imaging is the method undertaken to record and present 3D images or to give the image the illusion of depth. In fact, stereoscopic images include spatial information which tricks the viewer's brain into thinking that it perceives depth in the image. This is related to the virtual reality experience whereby the perception of depth and the interactive nature of the 3D images lead the viewer to feel like they are a part of the scene.

1.5 Research Aims

The principle aim of my research is to provide a new, effective compression technique. This technique allows to maximize on often competing, identified multimedia, data system qualities such as:

1. Compressed Quality
2. Compression Processing Time
3. Compression Ratio

Figure 1.2 identifies the relationship between each of the identified system qualities. The relationship of the balance between the performance parameter, one of my proposed methods provides high quality with a low compression ratio as lossless techniques. From the other side, other methods provide high quality with high compression ratio as lossy compression techniques.

Figure 1.2: Research aims

1.6 Research Objectives

In order to meet the main aim, this research work focuses on several research objectives that are essential for preserving the imperceptibility of the compressed images using the wavelet approach. The following key research objectives were identified in multimedia data compression:

1.6.1 To design and implement an efficient Image Compression Algorithm that makes a balance between:

a. Compression quality

b. Processing time

c. Compression ratio in real time

1.6.2 To develop a new Quality Enhancement Methodology for multimedia compression that is:

a. Compatible with the HVS perception approach.

1.6.3 To investigate case studies for analysis of various options for a mechanism of compacting data includes:

a. 3D Stitching Image

b. Big Data Storage based on DNA Computing

c. Subjective Quality Evaluation (Survey)

d. Data Compression using Steganography

1.7 Research Hypothesis

Data compression is not a new concept. In the topic of big data, the increased demand for a significant volume of data to be saved and handled. For big data the problem related to compression becomes critical. The challenge of significant data compression is particularly critical to Big Data Analytics, Cloud Computing and Internet of Things. This research, investigates and aims to validate the best approach to solve and manage the increased demand for Large Multimedia Objectives (LMOs) using optimal data compression techniques.

The proposed hypothesis of this research investigation is stated as follows:

> **"It is possible to improve performance of digital images compression, their storage capability, image quality and the perceptual quality applying compression and filtering mechanisms using wavelet techniques"**

1.7.1 Explanation

The impact of using compression techniques of big data is the main driver under situations because of the voluminous data that is considered. The hypothesis in this research has two sections as follows:

1- The hypothesis addresses through improvements compression techniques:

a. Reducing the size of Big Data

b. Improving data handling and storage

c. Improving processing (less bits to process)

d. Improving telemetry capability

2- Filtering improves:

a. The digital images quality by removing noise

b. Improve the Contrast of images

c. Improve the Brightness of images

1.8 Validation of Hypothesis

This thesis, considers big data compression techniques for huge data volumes so it can be stored and transmitted through data networks (such as TCP/IP) after enhancing. The main goal of compressing data is reducing data storage concerns and thus bandwidth transfer costings. Therefore, the sole reason for compression approaches is to ensure image quality while still lowering the data size required to store imagery. Measuring imperceptible factors of the compressed images is recommended for many approaches concerning with image compression. It can ultimately be determinable by subjective or objective evaluators as stated in chapter 2.

Digital media technologies and rapid advances in techniques to process digital signals have contributed to the digitization and easy distribution of a wide range of multimedia contents.

The work aims to reduce the memory resources needed by attaining a compression ratio is high enough, but does not diminish image quality by utilizing lossy and lossless methods of compression. In addition, the compression method is less time and power consuming due to the transmission of compressed data. Hence, compressing data both contributes to a reduction in data size and improves data security.

1.9 Specific Research Questions

The research questions are as follows:

1. Is it possible to improve performance using the weaknesses of HVS?

2. How to integrate HVS models efficiently in a wavelet based on multimedia data compression algorithm?

3. How can one solve the upload and download speed limits in the processing time for large data handling in cloud computing?

1.10 Research Contribution

1.10.1 Peer Reviewed and Published Papers

As a result of this research work the following conference papers and journals papers were published:

Hakami H.A. Zughaibi A.D. and Chaczko Z. "Review of HVS-based Image Compression Methods",International Journal of Computer Application (IJCA), 2015

Hakami H.A. and Chaczko Z. "Improve Data Compression Performance Using Wavelet Transform Based On HVS", Image and Vision Computing New Zealand (IVCNZ), 2016

Hakami H.A. and Chaczko Z. "Reversible Colour Compression Transform for Big Data System Using Human Visual System", 25th International Conference on Systems Engineering (ICSEng), 2017

Note: One more journal paper not yet submitted

Additionally, several other relevant publications covering the area of IOT applications include:

Hakami H.A. Chaczko Z. and Kale A. "Review of Big Data Storage based on DNA Computing", Asia-Pacific Conference on Computer Aided System Engineering (APCASE), Ecuador, 2015

Almarwani A. Alqarni L. **Hakami H.A**. Chaczko Z. and Xu M. "Door Wave Home Automation System", International Communications Satellite Systems Conference (ICSSC), 2013

Zughaibi A.D. Chaczko Z. and **Hakami H.A**. "Review of Human Motion Detection based on Background Subtraction Techniques", International Journal of Computer Application (IJCA), 2015

1.11 Organization of this Thesis

The complete report is organized henceforth, shown in Figure 1.3;

Chapter 1: Introduction to Data Compression Techniques.

The purpose of this chapter is introducing the background of Data Compression Techniques based Wavelet Transform. Follow by research problem and motivation which describes the problem and how can solve it. After that explain the research aims, research objective, research hypothesis and research question. Finally, a list of contribution.

Chapter 2: Literature Review of Multimedia Data Compression in Perspective.

In this chapter presents a general background of the main concept of multimedia data compression techniques for this thesis and provides the literature, state of art and techniques.

Chapter 3: Methodology and Mathematical Apparatus of Multimedia Data Compression.

In this chapter, it describes the methodology and mathematics of data compression techniques.

Chapter 4: Data Compression Experimentation.

In this chapter, it explains a novel proposed model of image compression Lossy Technique, Lossless Techniques and Enhancement Compression Techniques.

Chapter 5: Validation of Compression Quality

In this chapter, it will validate the quality of 2D and 3D images into different compression levels, then classify on data encrypted and present the experimental results of the proposed hypothesis.

Chapter 6: Action Research

In this chapter, it will provide the compressed stitching image, Big Data storage based on DNA computing, survey evaluation regarding to human opinion and how can the humans eyes see the differences between two images and present the data compression using Steganography.

Chapter 7: Final Conclusion and Future Work

In this chapter, it will provide a contribution and finally the conclusion which shows the current achievements.

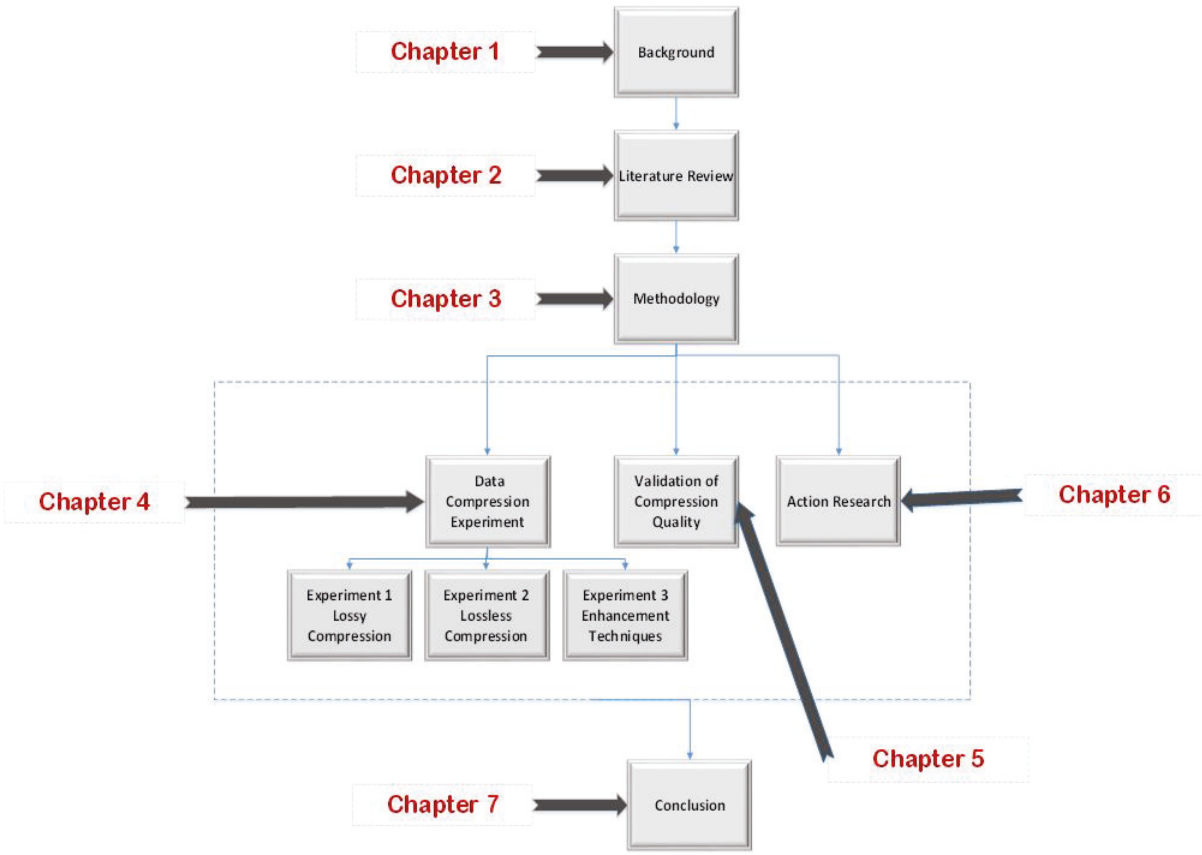


Figure 1.3: Organization diagram of this thesis

1.12 Summary

In conclusion, data compression is vital in computing and it is typically used by many software programs. This chapter explains briefly the background of data compression techniques and how it works in general. The data compression problem and assumptions necessary to solve this issue was discussed in this chapter. This is followed by the evaluation and motivation of data compression methods for them to be effective and efficient.

2 Literature Review of Multimedia Data Compression in Perspective

2.1 Overview

Rapidly developing information technology, along with the support of associated hardware and software increase the facilitation of widespread information throughout the internet. Obtained information is usually sent via the internet which is used as a communication medium for information technology specialists .. "Historically, the term of computer information technology referred to all technology systems associated with the gathering, processing, storing, and dissemination of information..." (United Nation Public Administrat (2012)). However, with the passage of time and ... progress of technologies, ...(it)...has acquired different connotations. The modern term, Information Technology (IT), ... is ... used generally to embrace both computer and communication technologies and their common basis – microelectronic technology and all the related software technology ..." (Beniger (2009)). Large data files, typically hinder data transmission, by using excessive bandwidth and imposing unreal demands on restricted data storage (GreenNet (2013)). To overcome this problem, data compression may overcome excessive storage and transmission budgets. The process of compression involves the conversion of data files that are large into a form that imposes reduced demands on restricted bandwidths and data storage sets – i.e., to save storage capacity and improve data transmission. "...Compression can thus save time and storage capacity costs..." (Pechura (1982)). Fitriya, L.A., Purboyo, T.W. and Prasasti (2017) shows that many compression algorithms can be applied, including:

- Huffman Coding
- Run Length Encoding
- Lempel Ziv Welch Coder and
- Shannon Fano methods

This literature review demonstrates a general background of Digital Data Compression Methodologies. Multimedia Digital Data Compression incorporates two processes: compression and decompression. In this part, the understanding of multimedia information compression procedure is given. The primary methodologies of multimedia information compression are distinctly classified as:

- Lossy (Eliminates certain data, particularly redundant information - in an uncompressed state, only a certain part of the original information is still there) and
- Lossless (All original source data is recoverable when the file is in an uncompressed state (Singh et al. (2016))).

While the literature says this non of the least above can not be actually absolute, the only absolute is lossy that means everything is lossy, but lossless means that is relative to the situation to particular contexts.

- Acceptable lossless (There are no such things is completely lossless, in fact it becomes a compromise otherwise it could be lossy files which is almost impossible to achieve).

"...Data compression can also be defined as the science of representing information in a compact form. These compact representations can be created by identifying and using structures that exist in the data (itself)..." (Gupta et al. (2016)). Some multimedia digital data compression techniques have been clarified, to the extent of identifying all principle necessary elements for any rigorous data compression. To this extent, valuable use of image compression has been established for large data of even "Big Data" ("...large amounts of data in which traditional data processing procedures and tools would not be able to handle.." (Trinidad (2016)) – see the following section for more details.

2.2 "Large" Data Versus Big Data

This section looks at the differences between "Large data" and the term "Big Data". Referring to Table 2.1, it shows a progression of data approximate file in term of size.

Bytes	In Units	Typical Meaning
1	8 B	A single Keystroke(non-accented) character, a number from 0 to 255
70	70 B	A line of text
1,000	1 kB	Half a page of unformatted text; a very short email; an icon or small button image
8,000	8 kB	Typical size of an organisation's logo as you might want it on a web page(about 200 x 200 pixels PNG or GIF)
30,000	30 KB	A 5-page word-processor document; a typical HTML web page; traditionally, the maximum recommended size for an image on a web page (maybe 640 x 480 pixels JPEG)
100,000	100 KB	The maximum recommended total of all the elements on a single web page, including images and HTML (some authorities say 30 or 40 kB instead)
500,000	500 KB	A 5-page word-processor document including a badly-chosen letterhead or logo image; a reasonable size for a PDF document someone might choose to download; two 1280x960 JPEG photos from a smartphone, too large for inline use in a web page
1,000,000	1 MB	1 minute of near-CD quality audio as MP3 or OGG; A 2048x1536 (4 megapixel) JPEG photo from a smartphone or digital camera, even if blurry because of low light; the complete comedies and tragedies of Shakespeare when compressed using bzip2
5,000,000	5 MB	A three-minute MP3 audio at a very high bitrate (256kpbs); 1 minute of low-resolution video, or of streaming from a video-sharing site; all the Wikileaks cablegate files released by mid-Dec 2010; a 20-page PDF which might include a badly-chosen cover photo; the complete works of Shakespeare (uncompressed)
10,000,000	10 MB	Maximum size of an email that you can expect all recipients to receive
25,000,000	25 MB	Maximum size of an email attachment received by GreenNet or Gmail (as of 2010); approximate size of the 26-volume 1911 edition of Encyclopaedia Britannica
100,000,000	100 MB	Uncompressed TIFF of a single A4 sheet at 600dpi. Note that this may be 100,000 times the size of the equivalent plain text. The kind of mailbox size or .PST file size at which corruption becomes more likely
700,000,000	700 MB	Maximum amount of data on one CD-ROM; a two-hour TV programme downloaded from BBC iPlayer
4,000,000,000	4 GB	Amount of data on a DVD-ROM or typical new USB flash drive ("memory stick") Maximum amount of RAM (working memory) a 32-bit processor can use directly
100,000,000,000	100 GB	Typical hard drive size on a computer as of 2009 (doubles about every 2 years)
2,000,000,000,000	2 TB	Large external backup hard drive as of 2010

Table 2.1: Large file size (GreenNet (2013))

Then "Large" data refers to a dataset that is typically larger than 25 MB transmitted at a predicted internet rate (TCP/IP) of about 100 mbps (FTTC – NBN) for that to be useful in most application. Fibre to the Curb (FTTC) is the newest technology being used as part of Australia's National Broadband Network (Choros (2018)). Fibre to the Curb will see NBN deliver fibre-optic into the telecommunications pit, promising 100 Mbps (Brown (2016)). Big Data refers to "... data that is high volume, high velocity, and/or high variety which requires new technologies and techniques to capture, store, and analysis" (Gandomi & Haider (2015)).

Big data platforms are major in offering accurate analysis for compression technology, which can drive decision-driving capability leading to increased efficiencies in operations, reductions in cost, and risk reduction to the user. Taking advantage of big data, an infrastructure requires the framework that manages and processes voluminous of unstructured plus structured data, that is real time and protects security and privacy (Bonde, P. and Barahate (2017)). Notably technologies in the space of market utilities by occupied by large organizations such as IBM, Microsoft, Amazon, IBM, Apache Software Foundation and so forth to deal with big-data solutions. Apache Hadoop is a framework that is open source, that can process and store big-data distributively through computer clusters. Thus, it is built to effectively scale from one server to many servers, offering localized storage and computation (O'Driscoll, A., Daugelaite, J. and Sleator (2013)).

Therefore, Big Data factors high velocity, great volumes and extensive varieties of data processing tools. Large data and Big Data includes the following:

- Structured data : Relational data, object data
- Semi Structured data : XML data
- Unstructured data : Word, PDF, Text, Media Logs

2.3 Multimedia Data Compression Overview

Several applications developed to process data involve significant amounts of alphanumeric data such as names, addresses, and descriptions of general inventory and accounts. Also requiring large storage capacity devices are applications developed for medical, legal and library use. As such, there has been a rapid increase in the availability of systems to handle this type of material (Reghbati (1981)).

In addition, the spread of technology communication networks along with applications for teleprocessing require the transfer of significant volumes of data over extensive communication links. Therefore, to minimize data needs and communication expenses, it is necessary to limit the amount of redundant data representation (Agrawal & Pateriya (2013)).

There are two main categorizations of data compression methods:

- Non-reversible and
- Reversible.

The non-reversible method involves reducing the data representation size while preserving 'relevant information'. The reversible method is different in that all information is treated as relevant, and the original data is recovered via expansion (Reghbati (1981)).

Large data sets generally represent unstructured data. However certain multimedia data sets contain representations of multidimensional data – generally in the form of 2D, 3D items. This does mean that the compression includes metadata (providing information about the data itself) for reconstructing the dimensional data into its 2D, 3D forms (Li (2017)).

Therefore, the importance of data compressing Large Data is not dimension increasing or decreasing but is about the need for compression efficiency which relates to more efficient algorithm computational mechanisms.

Wavelet Transform is the techniques of compression applicable to imagery to minimize the bandwidth required for graphics transmission. These wavelet techniques have been proven to be indispensable for image processing. For this reason, the wavelet transform is applied in this thesis as the technique of compression (Boix, M. and Canto (2010)).

From a historical perspective, the first reference to the wavelet in data compression is traceable to the mid twentieth century, during which Alfred Haar composed his thesis entitled: "On the theory of the functional systems" in 1909 (Haar (1909)). Later, Haar introduced a whole wavelet family, which incorporated the Haar wavelet (Haar (1910)), for the purposes of data compressing large data files and to this date remains the least complex method of employing wavelet theory. Post 1970s, a significant development in data compression utilizing wavelet theory has been credited to Jean Morlet, who created and executed the strategy of shifting and scaling the function of "exploration" of wavelets of constant shape" (Grossmann, A. and Morlet (1984)).

The late 1970s, with online storage of files becoming a basic activity, compression of software programs (source and executables) became popular utilizing the versatile Huffman coding (Kumar (2013)). In 1977 Jacob Ziv recommended fundamental pointer based encoding. Mid-1980's, the works presented by the notable Terry Welch (Ambadekar et al. (2015)), including the purported LZW calculation, quickly became the most popular technique for most broadly useful compression frameworks (Wolfram (2002)).

Meyer (1989,1999) showed the best way one deals with multi-resolution analysis is the designing methodology for the majority of feasible and relevant wavelets that are discrete, along with algorithm-based explanation for fast wavelet-transform, outlining the scaling wavelet capacity (Akansu, A.N. and Caglar (1992)) (Graps, A. (1995)). Ingrid Daubechies (1987,1992) developed the concept of groups of wavelets and multi-resolutions (Gao & Yan (2010)). In the late 1980s, issues with handling large and complex images turned out to be more common and new techniques of compression were invented. Around the same time Stephen Wolfram (1990) defined the strategy of the lossy compression (Wolfram (2002)).

Wavelet transforms are a superior method in image processing science which factors image enhancement, compression and detection of patterns. Wavelet transforms are implemented in such a manner as to obtain high frequency resolutions at the low frequency portions and good temporal resolutions at the high frequency portions of the signals. Image compression methodologies are widely used in converting data from big and sparse formats into a more compact and dense format (Oduola & Akujuobi (2017)).

Increased utilization of data intensive applications for multimedia web use means there is ongoing pressure to develop better methods for encoding signals and images, and that signal compression is given a central position in storage and communication devices. Lossy or lossless data compression is needed to lower the quantity of storage space required and to enhance the ratio at which data is transferred. Wavelet transformation presents a particularly useful image compression method (Kansal et al. (2017)).

Data compression is the system from which the information is converted into files of a smaller size that is efficient for transmission and storage. This is a revolutionary notion, because without compression, using graphics is not practical given bandwidth and storage restrictions. There are specific standards for graphics on the web (technologies associated with the use of the internet) and data compression is incorporated in those standards to ensure reduced digital data to represent a video or image such as JPEG and MPEG. Representation of binary numbers by digital data is the process which data compression incorporates.

To ensure fast streaming of data, increasing the bandwidth speed of the internet is an alternative solution although less ideal due to extensive cost (Uthayakumar et al.

(2018)). Data compression is therefore a feasible solution to fast data streaming. All compression algorithms come with its decompression counterpart which restores the file to its original state. Various types of compression algorithms have been developed.

Lossless algorithms and lossy algorithms are two classes of algorithms that are used for compression purposes. The lossless method of compression is where data is converted into its original form without loss of data. The lossy method is useful at providing higher compression ratios, however the data may not be converted into its original form because some of the data may be lost in the process. The methods are also useful to ensure minimum interference in image data quality.

For "proper" compression, image data is first converted into a different domain such as wavelet or frequency, then quantizing, and finally lossless-based encoding of the coefficients that are the transformed (Xiao (2001)).

The prime objective of almost all types of techniques of compression is shortening the data necessary to show an image while maintaining an average image quality level. The image files are compliant with compression because these show spatial redundancies and these also contain the data which in a sense could be considered irrelevant to the actual purpose of the data.

Image enhancement is a critical element of image processing. The process involved in this enhancement technique is about the pixel intensity changes in the original digitized imaging. Thus, the purpose of enhancement of images is the improvement of the perception or interpretability of data encapsulated in the images, or offering a "better" input-process for different automated processing platforms (Chanana et al. (2011)).

S. Yang et.al., discusses a mechanism to control the ratio of enhancement by Histogram Equalization (Yang, S., Oh, J.H. and Park (2003)). This is used in most image processing for image enhancement. In some images that are digitized, the features of interest are contained in a narrow range of greyscale in a relative sense. It is possible to use a point operation to enlarge the features of interest contrastingly so they now take up a greater portion of the grey level range displayed - also known as the term contrast enhancement.

Histogram equalization is a technique typically used to enhance image appearances, as the process requires seeking a greyscale transformative function which effectively generates an image outputted with uniformity or almost uniform histogram. Making the supposition that an image source is dark mostly, the corresponding histogram could skew to the lower-end greyscale, and all details are compressed into the histogram's darker end. If grey levels are stretched at the darker end, one produces a uniform histogram that is more distributed - the resultant image becomes clearer as a result. Grey scale 19 transformation function can be determined assuming the grey levels to be continuous and normalized to lie between 0 and 1 (Gomes (2008)).

This Research focuses on wavelet technology to optimize data performance compression. Moreover, compression method efficiency and the reconstructable high quality images are necessary in the fields of in the domains of remote-based sensitivity, archival of imagery and imaging of medical concerns. This becomes highly critical with image analysis in various engineering and biomedical fields. In those instances, image-based quality may be formed in a deteriorating manner that leads to blocky artifacts being inevitable, resulting in lossy image data compression. Therefore, image resolution enhancement techniques may be required for optimizing the image quality (Rathee & Vij (2014)).

2.4 Typical Data Compression Process

To restrict the electronic space which is used to show information, the repetition of identical sets of data bits is eliminated in various types of files. Similar blocks of information which are identical in any text or image file are reduced or removed altogether by encryption in a program which is specifically designed for such a purpose. The same program is then implemented to convert the data into its actual decrypted form. Compression ratios of 1:10 to 1:20 are achieved which result in lesser storage space and more convenient data transfer. Figure 2.1 shows the basic compression and decompression component framework. The compression component includes the input images which transform itself using a quantizer step into the encoder as a sampled image. Then the decompression component which includes the decoder goes the other way, followed by the dequantizer to obtain the compressed images.

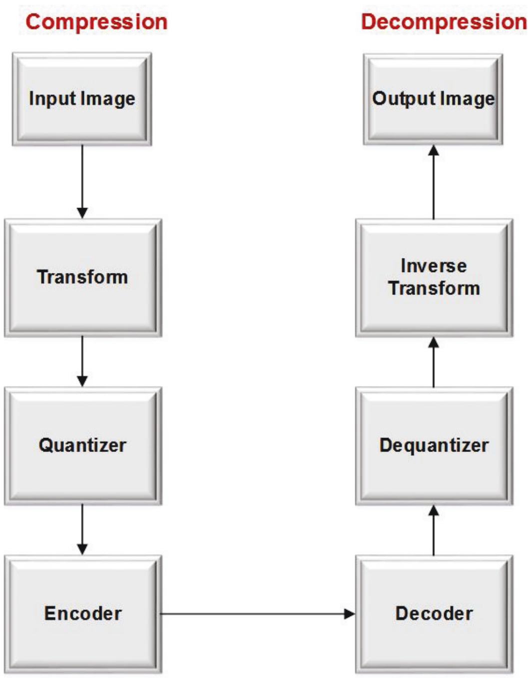


Figure 2.1: Typical data compression process

The encoder portion is employed to lower the psycho-visual, coding and inter-pixel redundancy of an image is inputted. In the initial phase, the transform applied to select the data to eliminate, thus reducing its band-width to shorten the inter-pixel redundancies. In the next phase, the quantizer block shortens the clarity of the transform's output concerning a set standard. In the final phase, a symbol decoder generates an algorithm for quantizer output and draws the output for the code.

2.5 Data Compression Categories

The prime objective of multimedia compression of data streams is to ensure that the volume of the data stream is reduced. However, quality is maintained to an acceptable level. The categories can be divided into two subsections:

2.5.1 Lossless Compression Techniques

High performance applications including telemetry, and medical imaging require lossless compression that relies on the precise retrieval of the originating source. The loss-less methods enable the input to be attained in its shape without data loss because data restoration to its original form can be achieved following data decoding. This method is undertaken two stages: decorrelation, and entropy coding. Entropy coding refers to a lossless coding process for digital data compression, achieved by using only a few bits to represent patterns that occur frequently and many bits to represent patterns to occur only rarely. Huffman coding is an example of entropy coding (Sethi et al. (2017)).

Decorrelation eliminates redundant space via run-length coding, SCAN language methods, and predictive and transform methods. Entropy coding such as LZW or Lempel-Ziv-Welch algorithm and Huffman coding eliminates redundant encoding (Rao, S. and Bhat (2015)). The technologies associated with the lossless method includes:

- Huffman coding: Is the process of assignment of long codewords to symbolics appearing in fewer frequency and reduced codewords to symbols appearing in greater frequency. The usefulness of Huffman codes is evidenced in how they create binary code-word groups of variable length when there is access to source PMF and alphabet. The Huffman coding is consistent of mean length and coders typically employ adaptive techniques and PMF estimations drawn out of coded samples (Sharma (2010)).
- Run Length Encoding (RLE) : Represents a basic type of lossless data compression whereby data runs (i.e., patterns where identical data value takes place in numerous consecutive data) are captured as one data value. RLE is therefore good for use with data containing several data runs (e.g. animations,

icons, and line sketches). RLE is not as useful however when there are limited data runs because it may result in a significant increase to the size of the file (Brar, R.S. and Singh (2013)).

- Arithmetic Coding: Involves the construction of code-words via the subdividing the spread of numerals between zero and one. When a symbol is given a code, the number range reduces by the amount which is the inverse proportion to the probability that the symbol will occur. At the point when the number range becomes suitably narrow, the number subdivisions stop and a binary fraction from inside the final spread is given to the code-word (Witten, I.H., Neal, R.M. and Cleary (1987)).
- Lempel-Ziv-Welch (LZW) coder: Is applied in various ways including text compression and signal compression. As a dictionary-based method, LZW established a match between the symbol sequence in the file and a dictionary-stored sequence, generating an index of symbol sequence. When a match for the symbol sequence cannot be found in the dictionary it is sent un-coded and a version is captured in the dictionary (Nandi & Mandal (2012)).

The technologies cited above are well-suited for multimedia data forms (e.g. medical records) that require the original form to be maintained (Anusuya et al. (2014)). That is, the technology enables the data sized to be reduced while leaving the data quality uncompromised (Rathee & Vij (2014)).

The techniques utilized in lossless compression of an image are grounded in both entropy coding theory and the theory of noiseless coding developed by Shannon. The key theoretical premise being that decoding data can be accomplished without error when, on average, there is a greater amount (by an arbitrary small numerical value) of data as per-source symbols at outputs than the entropy of information data per symbol, or entropy in other words (Yang & Bourbakis (2005)).

2.5.2 Lossy Compression Techniques

In the lossy compression technique, the original file cannot be recreated according to its uncompressed version. For higher compression, the quality is compromised in the lossy compression technique (Maini & Aggarwal (2010)). There are three stages of compression in lossy technique. The first one is coding transformation which enables a higher compression ratio, the second part is vector quantization and at the end used compression of fractal encoding. These techniques are implemented to control distortion that occurs during the compression process (Chawla, S., Beri, M. and Mudgil (2014)). The following steps are the lossy compression techniques:

- Transform Coding: Refers to compression for 'natural' data such as an audio signal or a photograph. A lossy transformation typically occurs whereby the copy is of lower quality than the original. During the process, certain information is selected to be discarded to lower the data bandwidth. The information not discarded is subsequently compressed using different methods. Although the process to decode the output is not expected to return an outcome that the same as the original input, there is the expectation that it is similar enough to warrant the coding process. Three 'transform' coding applications include (Penna et al. (2007)):

  - Discretised Wavelet Transforms (DWT)
  - Discretised Fourier Transforms (DFT)
  - Discretised Cosine Transforms (DCT)

- Vector Quantization (VQ): Refers to quantization methods associated with signal processing that enables the probability of density functions to be modelled via prototype vector distributions. VQ was first applied in the compression of images based on its action to divide vector points into groups based on proximity and an identical or similar number of points. Density matching in VQ is particularly effective for determining the density of highly dimensioned and large data sets (Vimala, S., Devi, K.K. and Sathya (2012)). Given that the data points are indicated in an index of the centroid nearest in proximity, a low error rate is associated with commonly occurring data, and a high error rate is associated with uncommonly occurring data. For this reason, VQ is acknowledged as good for the lossy compression of data, as well as useful for the correction of lossy data and for making estimates of data density (Saharan (2016)).
- Fractal Coding: Refers to the process whereby an image is first decomposed into segments via recognized image processing methods including edge detection, separation of colour, and the analysis of spectrum and texture (Hitashi, G.K. and Sharma (2014)). The next step is to determine the Iterated Function System (IFS) codes for each segment using a library of fractals. The library stores the codes as a compact number set, and the code for a specific image can be identified via a systematic process. The selected IFS code may then be applied to the stored sets of images to yield a suitable image output that closely resembles the original (Joshi, Manish, RajendraBelwal (2017)).

2.6 Data Compression Performance

Some of the better Data Compression properties that include the following:

- Storage Capability of Data Compression in Cloud
- Data Compression Ratio
- Data Compression Time
- Perceptual Quality of Data Compression
- Trade Offs

2.6.1 Storage Capability of Data Compression in Cloud

Cloud-based data compression storage provides open access to, and use of, configurable system resources and quality support services. First initiated in 1996, cloud computing is generally considered as a form of public utility based on its reliance on shared pools of resources to achieve a coherent and economic technology platform. Cloud computing is important to contemporary business and personal practices as it increasingly provides a link between resources and users that are not limited by physical boundaries (Jadeja & Modi (2012)).

As the increasing demand from users for data processing results in the need for increasingly more sophisticated computational functions, the number of companies to provide cloud-based services (e.g. storage and platforms) has also increased. Notwithstanding the benefits to users from such cloud computing services, they must be considered in relation to key challenges such as maintaining data security, controlling storage capacity, and task scheduling. Cloud-based data storage is particularly important given the seeming continuous demand for virtual space for the storage of large data sets (Sandhu & Kaur (2015)).

To achieve optimal outcomes in cloud-based data storage, the effective compression of large data sets is vital. Numerous data compression methods are available and play a key role in the efficient storage and transmission of data by reducing bandwidth and transmission time. It is generally acknowledged in the literature that the management of stored data using the cloud is most effective when lossless data compression methods are used (Yang et al. (2017)).

Some information loss from lossy data compression is generally accepted when it occurs during a video conference call or a photograph for example and is largely undetected by the human eye. However, information loss is not accepted in relation to important financial or medical data. Therefore, lossless compression methods are arguably superior to cloud storage because of limited data loss (Muneshwara M.S, Swetha M.S (2014)).

2.6.2 Data Compression Ratio

The ratio of compression is an essential construct applied for the measurement of relative differences in values of pre-compression as well as post-compression. The Equation 2.1 below shows the calculation of the compression ratio:

$$CompressionRatio = \frac{OriginalImages}{CompressedImages} \tag{2.1}$$

$$DataRatioSaving = (\frac{1}{CompressionRatio}) \times 100$$

$$100 - DataRatioSaving = CompressionRatio$$

The compression ratio difference between is the space required to store original and the compressed data. It is therefore beneficial that only that information should be stored that it is essential to bring the image into its original shape. Among the two compression techniques, the lossy technique compromises for the size and digital-image quality (Grgic, S., Grgic, M. and Zovko-Cihlar (2001)). The number of bits/pixel needed for a digital image on average is called the Equivalent measure which is a bitrate. Entropy is another effective measure of compression ratio. Larger measures of entropy would indicate higher compression and effect the compression ratio (Balakrishnan, K.J. and Touba (2007)). However, this is also dependent on the image input and content. For a better compression technique, it will have a higher compression ratio and achieve an image with good quality.

2.6.3 Data Compression Time

The presentation of visual data has time dependency which has to be considered in the process of compression. To achieve the multimedia ratio and compression system, the relationship of timings must be handled in an efficient manner. This aids in achieving the goal of reducing the size as well as time is taken. Although the transmission speed of upload and download limits in the time of processing and a drive to manage the concern of big data management (Goldstein et al. (2011)). Compression techniques are much reliable method to reduce the space over the Cloud as high demands for digital data leads to inefficient cloud storage. Compression techniques give benefits to the companies that deal with large data sizes over Cloud infrastructure thus reducing costs (Bhavya et al. (2018)).

2.6.4 Perceptual Quality of Data Compression

The qualities of a digital image are accessible subjectively and objectively (Cosman et al. (1994)). Objective methodologies mostly consist of computed distortion measures, with Reconstruction error is a notable practical measure. Imagery and visual data in their actualized form contain many elements which increase its size, and makes it harder to transmit owing to larger sizes and greater bandwidth needs. To contain this problem, image compression technologies are used, as it is well-known to reduce the dimension of representation by maintaining a degree of quality.

The procedure of losslessness includes the preparation of unique data into an indistinguishable yield, though reducing the overall data payload, inferring a quality image while size compaction takes place. Additionally, lossy compression factors a higher compression ratio proportion - however the result is a reduced quality of recreation because expansive data tends to be eliminated during the procedure. The compression procedure, information changes are made to an alternate space such as wavelets or via frequency components. Among the procedure stated, quality of digital imaging as well as ratios of compression is required. The quality of the digital imaging and ratio of compression are proportionately inverse through the whole computational stage. Thus, the greater is the ratio of compression means image quality is reduced. Such that the inverse is also correct for a compression-ratio that is lower. The quality of perception is noted as an effective measurement in the system of image-based compression; distortions in the image are defined by (Miyahara, M., Kotani, K. and Algazi (1998)):

- Quality Scale of Picture or PQS
- Opinion Score as a Mean or MOS

In this manner, significant quality is the perceptual impression of the image as the compression procedures take effect. Although Peak Signal to Noise Ratios (PSNR), along with the notable evaluator of Mean Squared Errors (MSE) as well are an important factor, they are referred to a higher-order factor of quality as they consider additional perceptible detail factors of an image (Mohammadi et al. (2014)).

There are differences present in various systems, methods and techniques when it comes to the evaluation of quality in Data Compression Techniques. These differences are mostly based on before and after the compression of images. For instance, the compression techniques applied to the compressed image can shrink data size without degradation of overall quality.

It is essential to ensure that no visual variation is seen among the original source and its compressed counterpart. The imperceptibility of this difference should be perfect as concerned by the Human Visual System (HVS). If the quality of the compressed image is great, then the compression ratio is also implied to be significant. Thus, the quality of compressed images should be evaluated because it is a vital metric in assessing the performance of the compression techniques (Dung (1998)).

The aim of image quality-based metrics is to evaluate and assess overall image quality through various quality indicators (Nisha, S.K. and Kumar (2013)). This is conducted to understand similarities among the original source and compressed variant, specifically their spatial and spectral properties. When applied in the technique of compression of images, the compressed data is referred to as the originating image source if the loss-less technique is used, while the compressed image is different the lossy technique is used. A categorization of the image quality metrics is broad, since it is based on the objective quality metrics aimed at providing computational metrics in assessing sameness among the original and its compressed version. Similarly, metrics for subjective quality is used as a basis for the image quality score through inspection of the images using the HVS (Pedersen (2011)). The following sections present a short introduction of the categories related to image quality metrics:

1. Objective Quality Evaluation

The objective metrics of digital image quality provide a predictive measure of visible differences in two images. The multitude of image quality evaluators is designed to make quantitative-based measures in the similarities between an original and its compressed version including pixel-based metrics such as PSNR, MSE, SSIM, UQI and HVS.

Objective quality assessment is performed using the most commonly used quality metrics. A brief description of these objective metrics used in this thesis is presented in the following sections:

- **Mean Square Error (MSE)**

MSE is determined by evaluation of mean of squared error, and error is defined as the differential of the imagery being evaluated. The representation of the formula is:

$$MSE = \frac{1}{n * m} \sum_{i=1}^{n} \sum_{j=1}^{m} (X_{i,j} - Y_{i,j})^2 \tag{2.2}$$

Where m is row value; n is column value of the digitally-sourced imaging, while X,Y are corresponding pixels in each imagery. It is apparent that the imagery size has to be the same, or scaled to achieve 1:1 pixel correspondence. Thus, the MSE is computed for each channel of the colour imagery and the mean of all 3 channel values to determine a singular output for every image-based pair (Wang & Bovik (2009)).

- **Peak Signal to Noise Ratio (PSNR)**

A typical measuring quality employed in compression technique is the highest signal-to-noise-ratio. Basic version of PSNR generally is known and applied in evaluating quality because of its simplicity, although many PSNR variants are available today (Rezazadeh & Coulombe (2013)). PSNR is shown as:

$$PSNR = 10 \times \log_{10}(\frac{255}{(MSE)^2}) \tag{2.3}$$

Where is 255 is the maximized intensity value of each pixel, such that the resolution is for 8-bit greyscaled images (Wang & Bovik (2009)).

- **Structural Similarity Index (SSIM)**

It measures the qualitative nature of the image developed on the initial image-based source. Nevertheless, this image is deemed to be distortion-free from compression or other factors. In here, an SSIM index is used to estimate perceived errors, wherein image distortion is a perceived alteration present in the structural information of the image (Wang, Z., Bovik, A.C., Sheikh, H.R. and Simoncelli (2004)). The basis of which is the estimation of pixels and the process of having interdependencies, specifically when the said pixels are close to each other in a spatial manner. Therefore, significant structure information related to the objects is provided based on the presence of interdependencies. The mathematical representation of SSIM is presented as:

$$SSIM\left(c,s\right)=\frac{\left(2\mu_c\mu_{s+C_1}\right)\left(2\sigma_{cs}+C_2\right)}{\left(\mu_c^2+\mu_s^2+C_1\right)\left(\sigma_c^2+\sigma_s^2+C_2\right)} \tag{2.4}$$

Where

$\mu_x$the mean of c

$\mu_y$the mean of s

$\sigma_x^2$the variance of c

$\sigma_y^2$the variance of s

$\sigma_{xy}$the co-variance of c and s

The value of SSIM is decimal, with $SSIM \in [1,-1]$ along with the value of one referring to an identical dataset.

- **Universal Image Quality Index (UQI)**

The Universal Image Quality Index (UQI) is simply calculated ranking of different applications for processing images. The UQI supersedes the use of traditional error summation techniques by determining image distortion based on the combination of three elements: correlation loss, luminance distortion, and contrast distortion. The formulas discussed below demonstrate the quality metric:

$$UQI(c,s)=L(c,s),C(c,s),S(c,s) \tag{2.5}$$

$$UIQI=\frac{4\mu c\mu s\mu cs}{(\mu 2c+\mu 2s)(\sigma 2c+\sigma 2s)} \tag{2.6}$$

Where

$L(c,s)=2\mu c\mu s\mu 2c+\mu 2s$ (Luminance Distortion)

$C(c,s)=2\sigma c\sigma s\sigma 2c+\sigma 2s$ (Contrast Distortion)

$S(c,s)=2\sigma cs\sigma c+\sigma s$ (Structural Comparisons)

Where $\mu c, \mu s$ denotes average values of both the compressed plus original imaging and $\sigma c \sigma s$ denotes standard-deviation for the two images. Moreover, σcs represents covariance for the two images.

The quality index present in the dynamic range is known as$[-1, 1]$ and the value for maximum similarity is 1. A high correlation is seen in various applications of the UIQI in relation to the subjective scores derived when certain experiments have been done (Zhou & Bovik (2002)).

2. Subjective Quality Evaluation

To undertake Subjective Quality Evaluation (SQE), observation of certain images is done. This is then followed by the evaluation or assessment of the images' visual quality. The problem lies in the different levels of visual sensitivity held by observers and the underlying changes seen in it. Despite subjective experiences, it is known that every objective image quality measure could not show a perfect impression as perceived by humans. It is therefore proposed by Stoica et. al. that subjective quality measures be used in depicting a genuine benchmark of performance, particularly for various tools for image-based processors (Stoica, A., Vertan, C. and Fernandez-Maloigne (2003)). Subjective measures pose higher reliability in identifying the actual quality of image for the principle that humans are the main definitive receivers of the message being subjected in almost all applications. Moreover, subjective testing offers the optimal methodology for the evaluators of quality of imaging in terms of certainty and reliability. Furthermore, structured experimental designs are used in subjective measures. According to some authors, this positions the human end user as an evaluator of image quality as they are the best party to do so. Subjective measures are also highly recognized methods because of the manner of quantifying the concrete quality perceived. During the process, the image quality is rated by the observers based on a reference image or a given quality or impairment scale. The images are rated based on an average score known as Mean Opinion Scores (MOS). This is considered as a measurement for subjective-based quality expressed as a strong measurement of quality. The MOS is computed by subjecting a test condition k (i.e. Compression Method), using the Equation 2.7:

$$MOS_k = \frac{\sum_{n=1}^{N} m_{nk}}{N} \tag{2.7}$$

Where m_{nk} reflects the score garnered by subject n when subjected to test condition k, while N denotes the total number of subjects (Streijl et al. (2016)).

2.6.5 Trade Offs

In this setup, the compromise is made between flexibility and efficient execution of the algorithm accomplishing the compression. Firstly, the ratio of compression is mainly configured to show the relationship between uncompressed and compressed information. Secondly, to accomplish the multimedia ratio and compression system, the relationship of timings must be managed effectively. Thirdly, the higher the overall resolution, more space is needed for storage. It is recognized the existence of an inverse relation between space and compression ratios. The image quality considers the user's perspective, so it is subjective in nature.

2.7 History of Image Compression Techniques based Wavelet Technology

This section endeavors to give a prologue to the most fundamental compression techniques in digital images. The most well-known image formats are GIF, PNG, GIF, JPEG and JPEG2000. Table 2.2 shows some of the key studies in image compression techniques by name, the author is organized in year order. The table includes performance analysis of the techniques, with the image compression techniques broadly classified into the categories as follow:

Method	Author	Year	Compression Rate	Value of Image Quality
Haar Wavelet	Alfred Haar	1909	4.1230	40.765
DFT	J. W. Cooley and J. W Tukey	1965	2.8632	40.3562
DCT	Ahmed N, Natarajan T and Rao K,	1974	7.1763	20.0263
Daubechies Wavelet	Daubechies I, Grossmann A and Meyer Y	1987	5.8326	36.1523
CWT	Christopher E. Heil and David F. Walnut	1989	4.2101	15.1230
DWT	Christopher E. Heil and David F. Walnut	1989	8.9984	61.4364
JPEG	Wallace, G.K	1991	6.2423	59.5018
VQ	Gersho A, Gray R.M	1991	3.2156	29.2833
Fractal	A.E Jacquin	1992	1.6958	29.0456
EZW	Jerome M. Shapiro	1993	5.9645	60.1243
Wavelet	Chan,Y.T	1995	5.3012	37.1401
WDR	J.Tian and R.O.Wells,Jr.	1996	6.2310	20.7140
SPIHT	A.said,W.A.Pearlman	1996	6.2423	50.5018
ASWDR	James S.Walker	2000	6.2102	30.9601
JPEG2000	D.Taubman and M.Marcellin	2002	9.9984	62.743
HS-SPIHT	Habibollah Danyali and Alfred Mertins	2002	1.2558	47.7179
SAR	Aili W, Ye Z and Yanfeng G.	2006	4.7101	24.4501
HCDC	H.Al-Bahadili, S.Hussain,	2007	6.2301	55.6952
ROI	Bartrina-Rapesta J, Auli-Linas F, Serra-Sagrista J and Monteagudo-Pereira JL.	2008	6.1235	23.1269
2-D DCT	Zhang Q, MengN.	2009	7.0165	41.3210
BCWT	Jiangling Guo	2010	7.3216	44.4569
2D Wavelet	Deokate MB, Patil PM	2011	8.2360	60.1245
JBE	Suarjaya IM.	2012	7.1235	50.1230
ECG	Nidhal K. El Abbadi, Abbas M. Al-Bakry	2013	7.3692	12.3256
CSE	Beliveau M, Dube D.	2014	6.1233	22.0123
SeLIC	Alfred Bruckmann and Andreas Uhl	2015	30.50	27.50
DPCM	Dr.Ashwaq T. Hashim, Dr.Suhad A.Ali	2016	29.12	42.26
Modified DWT	Ali Al-Fayadh	2017	5.19	36.63
OGWO with MHE	Priya Vasanth Sundara Rajan, Lenin Fred A	2018	94.58	44.71

Table 2.2: History of image compression

2.7.1 Wavelet Technology in Image Compression Techniques

The Wavelet algorithm is utilized in computerized signal handling and for image compression to divide data into various frequencies. Specifically, wavelets identify the signal at different scales or resolutions; that is, at multi-resolutions. Wavelet transforms are considered within a limited interim and an estimation of zero. The wavelet transform is fundamentally about providing a self-assertive function set arbitrarily at one (t) as the superposition of wavelet arrangements or premise capacities, i.e. infant wavelets. Wavelets drawn from a singular wavelet, i.e. mother-based wavelet, via scaling (e.g. enlargement or withdrawal) and shifts (e.g. interpretations) (Chun-Lin (2010)).

The Discrete Wavelet Transform of a certain signal length $x(n)$ that has N parts for example is represented via a NxN matrix (Dhawan (2011)). DWT also helps to preserve image quality (Hakami, H.A., Alzughaibi, A.D. and Chaczko (2015)).

Wavelet Transform (WT) provides a realistic image via a suite of wavelet functions (wavelets) that have different scaling and shifting. The breaking down of a image into wavelets involves two waveforms: the wavelet function that shows high frequencies to make a comparison of point-by-point sections of an image and the scaling function for the lower frequency or sections of the image (Tammireddy, P.R. and Tammu (2014)). In mathematical terms, the presentation of wavelet ψ is in the following Equation 2.8:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi(\frac{t-b}{a}) \tag{2.8}$$

Where a and b are scaling and shifting parameters, respectively.

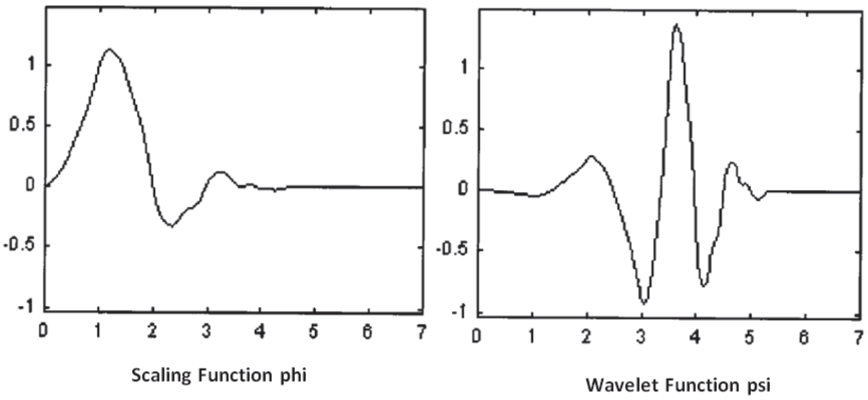


Figure 2.2: Scaling and wavelet function (Grgic, S., Grgic, M. and Zovko-Cihlar (2001))

Figure 2.2 presents two waveforms of a family group discovered in 1980 by Daubechies: the figure to the right provides more point to point parts while the other figure shows the smoother components of a realistic perspective. The time hub is used for the interpretation and scaling of both waveforms to generate an array of wavelet transforming on changing spaces and scale attributes. Each wavelet includes an approximately close cyclical pattern, with a reduction in the frequency also causing the wavelength to increase. Higher frequencies are altered by shorter functions (i.e. low scale); whereas, lower frequencies are altered longer functions (i.e. high scale). Within this calculation, the deteriorating wavelet is shifted to the deteriorating function space. The outcome of WT is array of wavelet-based coefficients that assesses the wavelet effects in these areas and at these levels (Antonini, M., Barlaud, M., Mathieu, P. and Daubechies (1992)).

An integral element of the wavelet is the multi-resolution decomposition, whereby the imagery may be reconfigured at the targeted resolution following decomposition by the wavelet. To operationally run this outcome and do it precisely, both a HPF or High-Pass Filter and LPF or Low-Pass Filter and a must be the chosen tools to precisely split the frequency-based range. The two filters are referred to collectively as the Analysis Filter pair and during the initial phase, lower frequencies of the row are achieved via the application of an LPF to each data row. The LPF is a half-banded channel and yields information comprising frequencies in the initial 50 percent of the starting range of frequency. According to the Sampling Theorem by Shannon, the may be subject to further examination by two to ensure that the information yield includes a large section of the initial tests. In addition, the HPF is attached to the same information column which isolates the high pass sections and positions them adjacent to the low pass sections (Rohit, A., Madan, L.S. and Nidhika (2011)).

A similar application is undertaken for each row. Following this, separation occurs for each column to achieve four information groups indicated as:

- L.L. (Low - Low)
- H.L. (High - Low)
- L.H. (Low - High)
- H.H. (High - High)

It is also possible to create many more sub-bands via further decay of the LL band via the process described above (Walker, J.S. and Nguyen (2001)). This may be linked to a certain level resulting in pyramidal decay above the LL band where the largest amount of decay is important. Conversely, for other groups of less significance, the importance is in the abatement level from the pyramid's high point to its low point (Pandey (2014)).

2.8 Image Enhancement Techniques in Compression Domains

The process of enhancing images is designed to assist a person's ability to perceive information or interpret images, and to facilitate improved input for other methods to process an image. An image generated in a natural environment with a high dynamic range will include light and dark areas. Because of the increase in dynamic range, it is difficult for human eyes to see the images. Enhancement of an image is performed to improve image quality and to modify image attributes to increase its suitability for a specific task or a specific observer (Singh et al. (2013)). Image enhancement is basically divided into two main categories:

1. Frequency domain.
2. Spatial domain.

Spatial domain technique addresses the image's pixel values; whereas, the Frequency domain technique deals with the Fourier transform to enhance an image.

In the recent decades, consistent improvements are being made in both image and video processing enhancement and compression methods to optimize the storage space and transmission of visual information. The main aim of image quality enhancement and compression is to minimize the image data that is irrelevant to store or convey data in a suitable efficient way (Chaudhary & Patil (2013)).

In the last few years, the demand for the development of multimedia grows, resulting in the shortage of bandwidth and storage space. Therefore, the concept of image enhancement and data compression is very important to save the storage space and bandwidth during transmission. In information theory, source coding used for compression is a method of coding the information using a lesser number of bits (Bhatti & Kim (2016)).

2.8.1 Related Work for Image Enhancement Techniques

Mohanapriya and Kalaavati introduced methods for enhancing spatial domains in addition to an algorithm via an analysis of the medical image quality (Dixit & Khandelwal (2014)). (Bedi and Khandelwal) provided an overview of the methods for enhancing images in the spatial domain. To clarify, they classified the processing techniques based on the representative image enhancement methods (Singh & Mittal (2014)). Furthermore, (Chanana, parneet Kaur Randhwa,Er.Navneet Singh) drew attention to various practical enhancement techniques for Scanned Electron Microscope (SEM) images and the results from experiments. SEM images include both dark and light areas (Chanana et al. (2011)). (Adin Ramirez Rivera, Byungyong Ryu, Oksam Chae) developed a content attentive algorithm to enhance dark imagery, provide sharper edges, expose greater detail in textured regions, and maintain the smooth areas (Rivera et al. (2012)). (Rajesh Garg, Bhawna Mittal, Sheetal Garg) introduced a framework to enhance images that draws on the Histogram Equalization techniques. Various image based enhancement algorithms are implemented and subject to comparison including DSIHE or Dualistic Sub-Image Histogram Equalization, CLAHE or Contrast Limited Adaptive Histogram Equalisation and DHE or Dynamic Histogram Equalization (Garg et al. (2011)).

(Komal R. Hole, Vijay S. Gulhane, Nitin D. Shellokar) provide a general outline of canonical genetic algorithms in addition to reviewing the image pre-processing task. The authors describe several approaches utilizing the genetic algorithm to obtain an image with natural contrast (Hole et al. (2013)). (Arun R, Madhu S. Nair,R. Vrinthavani and Rao Tatavarti) investigated a novel technique whereby alpha rooting is performed to enhance even low-contrast images (Mokhtar, N.R., Harun, N.H., Mashor, M.Y., Roseline, H., Mustafa, N., Adollah, R., Adilah, H. and Nasir (2009)).

2.8.2 Image Enhancement Technique Categories

As previously mentioned, image enhancement methods fall into the categories as follows:

- **Spatial Domain Technique**

The spatial domain technique focuses directly on the x smallest part of the image; that is, the pixels. Each pixel corresponds to a modified value determined by the problem area. The goals of this technique are to improve image information perceptibility and to enhance the structural features to support better image quality (Dixit & Khandelwal (2014)). Spatial domain techniques alter the data array of the image via a point processing approach or an area processing approach. This technique typically manages spatial-based frequency, that is the differential among high and low frequency values of a pixelset that is contiguous (Singh & Mittal (2014)). There are two categories of methods to enhance images via spatial domain techniques: Global and Local Image Enhancement.

Global methodologies primarily utilize modifications in the histogram to manipulate the entire range that is dynamic by altering the image histogram. This method is attractive for its simplicity and the minimal effort required for computation. It is however often the case that the enhance process is undertaken on smaller areas. Enhancing local image techniques are often utilized in these applications. Several spatial domain methods are available and are typically categorized into global or local image enhancement groups. A notable global enhancement methods is Histogram Equalization (HE), a simple and commonly-used technique. HE increases the image's dynamic range by assigning intensity values to input image's pixels for the output image to include an unvarying distribution of intensities. HE also improves the overall contrast in the image (Chaudhury, S. and Roy (2013)).

The histogram's Cumulative Density Function (CDF) is applied in HE as an intensity transfer process. This technique improves the contrast via the distribution CDF throughout the whole dynamic range. The subsequent smooth distribution does however introduce artifacts into the image's smooth areas. Furthermore, there is no consideration of the boundaries which diminish output image sharpness. The main disadvantage of HE is that it generates a washout effect in situations where the original histogram is unable to occupy the image's whole dynamic range. Hence, numerous methods based on HE is available to circumvent the disadvantages associated with the original technique.

Adaptive Histogram Equalization (AHE) is a local digital imaging enhancement-based methodology that extends on traditional HE techniques. AHE improves image contrast via the transformation of the image's intensity values (Pizer et al. (1987)). In contrast to HE, AHE focuses on small regions of data regions (i.e. tiles) instead of the whole image. The contrast in each tile is enhanced for the output area histogram to approximately reflect the chosen histogram. Bilinear interpolation is then used to combine neighbouring tiles to remove artificially created boundaries. The image histogram in AHE is separated into different modifiers to align across boundaries, and to produce better outcomes in images that are dark. Contrast, particularly in homogeneous regions, may be restricted to eliminate the noise amplification existing in the digital image (Singh, K. and Awasthi (2013)).

Several other methods drawn from spatial domain techniques including Bi-Histogram Equalization (BHE) and Laplacian are also available. BHE divides the histogram into two sections dependent on location of middle point, or mean. HE is then utilized to independent enhance each section. The original image's intensity mean is maintained via BHE as it restricts over-enhancement. There is still the production of unnatural images however. Laplacian can be utilized to improve the image's edges; thus, characterizing it as an edge enhancing algorithm. It carries out local enhancement of the pixel's brightness resulting in an image with enhanced local contrast at the rectangular domain's edge. Each domain is passed through the HE to enhance the level of brightness (Chaudhary & Patil (2013)). The following Equation 2.9 is the spatial domain for image processing over the image pixels:

$$g(x, y) = \tau[f(x, y)] \tag{2.9}$$

Where

$f(x, y)$, $g(x, y)$ are inputs and imaging being dealt with the math map τ elaborated via (x, y). When the map or operator is considered on a random co-ordinate point (x, y) to obtain the point of process at equivalent co-ordinate being (x, y), the math map τ is known as mapping of intensities, or transformations of greylevel (Das (2015)). If r and s is the random point's intensity before and after the transformation process, Equation 2.10 can be rewritten as:

$$s = \tau[r] \tag{2.10}$$

- **Frequency Domain Technique**

The Frequency Domain technique focuses on image Fourier transforms. Frequency domain enhancement is a relatively straightforward process whereby the image

Fourier transform for enhancement is computed, then the result is multiplied by a filtration process, and the inverse transform is adopted to create an image that is enhanced (Shapiro and Stockman (2000)). Hence, the frequency domain technique initially computes the image Fourier Transform prior to performing all enhancement operations (Pratt (2001)). The processes for enhancement are undertaken to adjust the image contrast levels and brightness levels, or distribution of greylevel. Thus, the output image pixelised value is modified in alignment with the transformation operation on the input image values. Convolution theorem forms the platform from which to perform domain of frequency methods. Domain of frequency relationship is provided by convolution theorem as stated:

$$G(u, v) = H(u, v)F(U, v) \tag{2.11}$$

Where $G(u, v)$ is the image that is enhanced, $F(u, v)$ is the image that is inputted and $H(u, v)$ is function of transfer. Hence, these are the essential sequences applicable for filtering a digital image in the domain of frequency. Image-based enhancement problems is viewable in equation form as stated earlier. The goal is choosing a transferring function changing the imagery in a manner that imagery features are eventually enhanced. Typical example cases include edge detection and noise removal (Agrawal et al. (2014)).

2.9 Single-Pixel Image Compression Algorithm

The processing of digital signals and multimedia computing is applied in production and processing of digital images. To capture and store raw images, the devise must have available a relatively large amount of storage space. In addition, it is necessary to have greater network bandwidth during transmission. There is limited availability of image compression algorithms within the lossless image compression grouping that can obtain the compression ratio required without first having to transform the digital image from its domain in its spatial dimension. As the name suggests, compression of digital imaging is the step taken to lowering the information volume required to store and transmit the image. This process facilitates a reduction in the network or satellite transmission bandwidth (Dhawan (2011)). A pixel value matrix is used to represent the image whereby each colour pixel is signified as an integer in range of 0 through to 255 and which occupies 8 bits. The RGB, or Red, Green & Blue image consists of primary colour planes that are three in total. The test images used to test the proposed algorithm are 24 bits represent the (planes used for colour depth) of the DLP colour (Tammireddy, P.R. and Tammu (2014)).

It is also possible to use single-pixel detectors as imaging tools via structured illumination processes. An object's image is achieved in this process by establishing correlations between the altering light field and the measures of the signals using a photodiode. This century has seen extensive research in the field of ghost imaging and computational imaging using single-pixel detectors. Notwithstanding that the origins of each research area differ, the ways in which they overlap can be demonstrated. To generate an image ghost imaging originally utilized two correlated light fields and two photodetectors. During the process, the non-spatial resolution detector collects the light from one field to have earlier interacted with the object. The high spatial resolution detector collects the correlated light which did not interact with the object. Neither the non-spatial resolution nor the high spatial resolution detector can independently generate an image the object, but when the measurements from each detector are combined an image can be generated.

This method differs from the classical ghost imaging technique in that it is relying on a digitized light projector (DLP). Specifically, the DLP offers binary structured spatially incoherent illumination that can be imaged to the scene's plane using a 55 mm lens. A DLP also has a digital micro-mirror device (DMD) along with three coloured (RGB) light emitting diodes (LEDs). The total reflection intensity from the scene for every single incident pattern is positioned on a composite dichroic beam splitter (X-Cube) through the use of a large collection lens. The RGB light outputs can be spectrally filtered via the dichroic beam splitter to enable their measurement via three single-pixel unfiltered photodetectors. This process is presented in Figure 2.3. The measurements of the photodetection signalisation is recorded using Analogue-to-Digital converting system. This data is subsequently used for reconstruction of the image using the appropriate algorithm. To retrieve images quickly, the scene needs to be illuminated quickly using differently structured light fields. The light projector's DMD has an array switch rate of 1440 Hz, supported by 60 Hertz framerate and 24bit DLP planes (to achieve colour-based depth). Given that binary illumination patterns are only needed, all three of the projector's LEDs can be operational permanently and can exploit the colour planes to exhibit 24 disparate images that is binary in every frame (Welsh et al. (2013)).

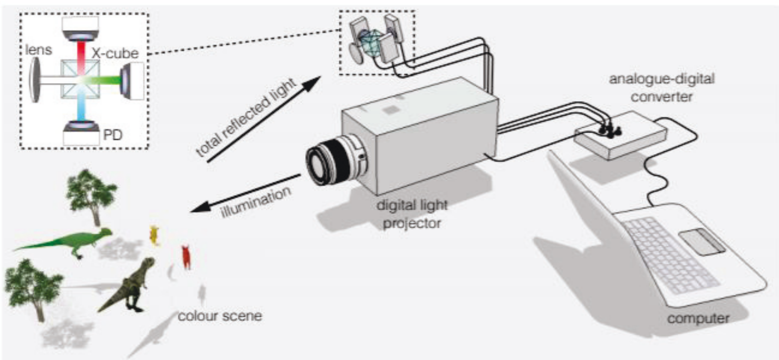


Figure 2.3: The system experiment's schematic for the imaging of coloured scene in (Welsh et al. (2013))

2.9.1 Image Reconstruction

The detection of single-pixels to perform imaging requires two reconstruction algorithms for data processing: Iterative and Inversion algorithms. Iterative algorithms provides a defined estimation of a particular scene following every measure; whereas, inversion algorithms bulk process full information sets to identify the optimal resolution for unknown sets. Each algorithm represent the final reconstruction resolution as $N = x \times y$, where x & y equal the pixel number utilized for illumination in the x dimension and y dimension, respectively. Each iteration (i) is represented by a single 2D pattern of intensity $I_i(x, y)$ that is projecting on the object considered. The matching reflective intensities (i.e. signal of voltage), at frequency spectral value µ, undergoes measurement for every photodetector's single pixel element, $S\mu_i$. Hence:

$$S_{\mu i} = \int I_i^{'}(x, y) R_\mu(x, y) dxdy \tag{2.12}$$

Where $R_\mu(x, y)$ is the scene's function of reflection for frequency of spectrum µ, while $I_i'(x, y)$ represents the pattern in 2D following the propagation stage. For this instance, because the modulation is imaged on the plane of the object; $I_i'(x, y) = I_i(x, y)$. If all of the scenes is situated inside the viewing field of the detector, the signal under measurement is proportionate to the projected reflectivity of the scene onto the pattern of illumination. This is an effective factor of weighting in the algorithm used for reconstruction of an image. The three main image reconstruction algorithm types are as follows:

1. Iterative Image Reconstruction

In the reconstruction of iterative images, normalizing the photodetector signals improves the reconstruction of the image (Ferri et al. (2010)). Experiments demonstrate that normalizing the signals can be achieved via the maintenance of equal white to the black ratio for each pattern illuminated and acquisition of the differential signal between successive positive and negative patterns (Sun et al. (2012)). Iterative algorithm utilized was a traditional ghosting image algorithm defined by:

$$O_\mu(x, y) = ((S_\mu - (S_\mu))(I(x, y) - (I(x, y)))), \tag{2.13}$$

Where $O_\mu(x, y)$ is the scene-based estimate. The mean differential signals trends to 0, as each pixel in a mean pattern that is differential, hence Equation 2.14 can be re-expressed as:

$$O_\mu(x, y) = \frac{1}{M} \sum_{i=1}^{M} S_{\mu i} I_i(x, y), \tag{2.14}$$

for M samples. The outcome of the reconstruction of our iterative image is presented in Figure 2.4 for around one million measurements. To obtain the full-colour image, the last 3 images that are reconstructed by the detector were combined matching the RBG colour channels.

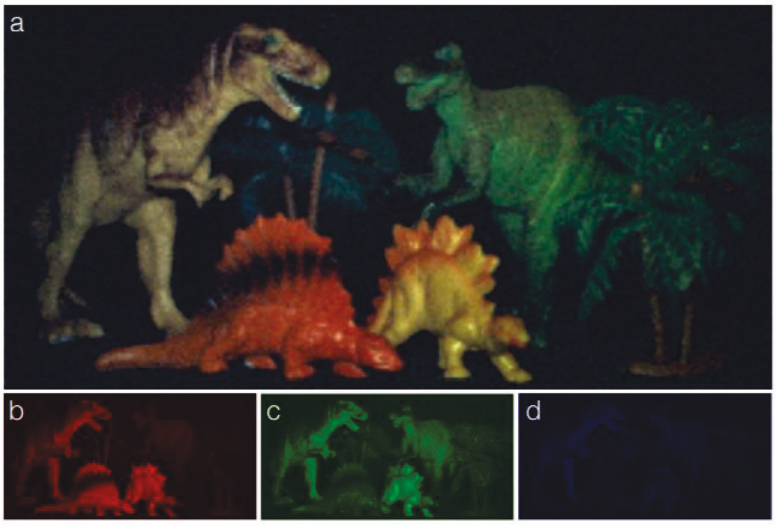


Figure 2.4: Full-colour iterative reconstruction of a 3D scene (Welsh et al. (2013))

2. Inversion Image Reconstruction

Regarding inversion algorithms; 2D patterns can be reshaped into a 1D array, I_i, to create a matrix of measurement, I, that includes all of the patterns that are projected. Thus,

$$I = [I_1 I_2 ... I_M]^T \tag{2.15}$$

So similarly; the signals that are measured can be expressed as a vector of columns:

$$S_\mu = [S_{\mu 1} S_{\mu 2} ... S_{\mu M}]^T \tag{2.16}$$

such the concerned problem is realisable as set of equations that are linear given by:

$$I_{O\mu} = S_\mu \tag{2.17}$$

Where O_μ represents an unknown set that, when in the process of recovery, may be reconfigured to $O_\mu(x, y)$, to represent the spectral frequency µ estimation of the scene. In instances where $M \succeq N$, least-squares methods are used to achieve a resolution. As the resolution of the imagery increases however, the size of I, results in the performance of this reconstruction being highly intensive computationally; whereas, addressing this issue by utilizing a lower number of measurements than the resolution size leads to problems whereby the quality of the image reconstruction declines rapidly (Welsh et al. (2013)).

3. Compressive Sensing

Compressive Sensing (CS) is proposed as a technique to reduce signal dimensions considered sparse or compressible within a particular basis representation. 'Sparse' is to be understood as meaning that only a relative few representing coefficients are non-zero. In contrast, 'compressible' is to be understood a fast decay in the coefficient's magnitude based on a power law. Therefore, a sparse signal can offer a satisfactory approximate of the signal. A projection of the signal is made onto a low-dimension space in the CS paradigm, leading to a measurements vector. In cases of a sparse signal, an exact reconstruction can be achieved from the measurements vector (Donoho (2006)). In cases of noisy measurements or when the signal is compressible rather than sparse, an approximation of the original signal is produced in the reconstruction. Natural images are suitable for CS because they are fundamentally compressible in either the frequency or wavelet domain (Yuan & Haimi-Cohen (2017)).

The amount of measurements required to faithfully reconstruct an image can be reduced by employing compression-based sensing techniques (Katz et al. (2009)) of which there are many different approaches. The experiment in (Welsh et al. (2013)) employs the $\ell 1$ magic toolbox for MATLAB. When employing this method, system representation must be an appropriately sparse basis. As a result, a Discrete Cosine Transform of 1D (DCT) was conducted on every pattern that is reshaped I_i whereby $I \Longrightarrow I_{DCT}$. The problem that is not conditioned can be stated:

$$I_{DCT} O_\mu^* = S_\mu, \tag{2.18}$$

Where O_μ^* is a 1D vector that contains the unknown set, for the scene at the frequency of spectrum µ, in the space of DCT. O_μ^* solution is provided when one minimizes as follows:

$$\frac{1}{2} \|S_\mu - I_{DCT} O_\mu^*\|^2 + \lambda \sum |O_\mu^*| \tag{2.19}$$

Pre-conditioned gradient methodologies that are conjugated are used, where: λ represents a regularization parametric (Koh, K., Kim, S.J. and Boyd (2007)) with an assigned value of 0.01 to achieve optimum performance. Conducting an inverse DCT on O_μ^* including appropriate reshaping leads to a scene solution, $O_\mu(x, y)$.

These compressed sensing methods means the quality of the reconstructed image is maintained, despite a highly ill-conditioned equations system, by exploiting the sparsity in the natural images. In Figure 2.5 compares the iterative algorithm and the CS method for the reconstruction of a coloured scene, 128×64 pixel resolution, for progressively more iterations. CS techniques enable the construction of a high quality image for 6000 total iterations (10 seconds or fewer to acquisition). This connects to around 75% of the Nyquist limit. When comparing this to the iterative algorithm to achieve the same iteration numbers, for enhanced digital-image contrast and quality to expectations (Welsh et al. (2013)).

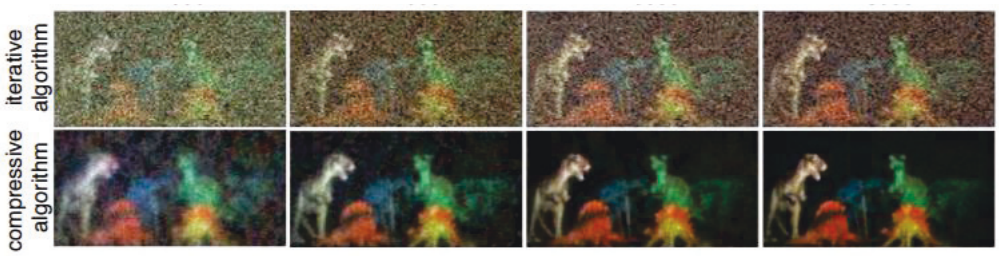


Figure 2.5: Comparison of coloured image reconstructions with pixel resolution of 128×64 (Welsh et al. (2013))

Computation-based imaging with 3 detectors of single-pixels may be utilized to create complete colour images of larger scene sources after only seconds of acquiring the data. Utilization of a light projector that is digital and an appropriate computer-based algorithm enables structural illumination to be achieved quickly; that is, short acquisition times, suggesting various alternative imaging applications may be developed. In addition, utilizing CS methods has been shown to significantly improve the quality of the image when maintaining the amount of measurements lower than the limit of Nyquist. Different types of imaging solutions emerge from the fact that additional photo-detectors can be accessed at low cost and that DMD technology has a large operating bandwidth. They include hyperspectral imaging and imaging at wavelengths at which there is only limited CCD or CMOS imaging technology. Moreover, single-pixel photo-detector use may provide low data requirements to send images if both parties are aware of the patterns utilized to produce them.

2.10 Multidimensional Compression for 3D Objects

Multidimensional compression is commonly applied in scientific research. It requires the development of a suitable arrangement to facilitate effective compression of the multidimensional array that uses relatively low memory storage. The main goal is to compress the multidimensional array via wavelet transform and can be used to manage large multidimensional sets of data. Multimedia needs require compression methods that are efficient for large data files (e.g. images, videos, and 3D data).

Although the relative costs to store data has steadily decreased in recent years, the volume of image and video generated data has increased exponentially. This is particularly apparent for large data repositories (e.g. YouTube and cloud storage). The consistent growth in network traffic and the storage needs of users suggests data compression algorithms will have a significant impact on data centers in terms of bandwidth, storage space, and energy use.

Data compression is increasingly important in modern times due to the ever-increasing demands for data storage. Advancing technologies provide more sophisticated tools to manage stored (Otoo, E.J., Rotem, D. and Seshadri (2007)). In this thesis, with three common 3D image compression techniques as follows:

2.10.1 3D Scanner Images

Large data sets are yielded from high resolution multidimensional images. 2D methods are regularly applied to images for compression and analysis, but they often neglect the information coherence in upper dimensions that can be manipulated to achieve better compression. For the compression, visualization and analysis of large 3D point clouds, the process is typical to convert the 3D images to Digital Surface Models (i.e. Raster Grids or Triangulated Irregular Networks). Image compression facilitates a reduction in the size of the bytes required for a graphics file while avoiding corruption of the image to the point where it becomes unacceptable. Three strategies are typically associated with compound-image compression, namely: block-based, object-based and layer based. The extent to which compression of the compound image or report is corrupted is associated with file capacity and transmission (Vasanth et al. (2018)).

Compression methods are typically applied in the area of computer-based graphics along with multimedia. The compression operation is generally performed on image formats including Joint Photographic Graphics (JPG), Portable Network Graphics (PNG) and Bitmap (BMP). The compression algorithm applied to the digital images is defined by each format. Like image compression, 3D object compression has developed extensively over the previous 10 years in the field of 3D computer graphics. Several methods for compressing 3D objects to support efficient storage are identified and discussed in the literature (Peng et al. (2005)).

To maintain a satisfactory degree of realism it is typical for most computer graphics applications to rely on a complex and well-detailed model. In turn, to achieve the highest levels of detail desired it is necessary for the models to be developed or obtained at high level resolution. It is not always the case however, that the full complexities of the model are utilized. Therefore, given that a correlation exists between the computational costs linked with the employment of the model and the model complexity itself, it is worthwhile to ensure less-complex versions of the model are available. Notably, the work currently being put into the development of surface simplification algorithms aims to automatically create simplified models.

Similar to a lot of the work currently being undertaken in this field, our aim is to simplify polygonal models. Based on the assumption that the model comprises triangles only, it is our belief that no generality will be lost because the preprocessing phase will include the triangulation of each polygon contained in the model. Improving the overall reliability of results means the intersection of the corners of two faces will be classified as sharing a single vertex instead of applying two separate vertices that are connected in space (Garland & Heckbert (1997)).

2.10.2 3D LiDAR Compression Techniques

Airborne Light Detection and Ranging (LiDAR) facilitates the collection of extensive point data from sampling terrain elevation as expected of Figure 2.6. Storage and distribution of the collected point data is typically accomplished using LAS format. An increase in LiDAR's sampling density correlates to an increase in file size. Although LAS files already contain millions of points, it is expected that this will increase to billions of points. Aircrafts fitted with laser-range scanning technology (LiDAR) gather exact elevation data of cities or counties. This is accomplished by more than 100,000 laser pulses being 'shot' at the location surface each second to measure resolutions at more than one point per square metre.

The data are then often used to create digital elevation maps which are applied for several purposes including: the assessment of flood hazards, for planning solar and wind installations, to conduct inventories of forests, and for the maintenance of power grids, etc. The amount of LiDAR data gathered is problematic however because it subsequently requires the storage, processing and distribution of billions of elevation samples. In terms of function, for every laser pulse emitted, the returning signal's waveform is recorded on the scanner. The waveform's intensity peaks match the locations where the laser makes contact, with the portions reflected the plane's sensors. Multiple peaks may be apparent given the capacity of the laser to hit different surfaces including tree branches, antennas, and birds etc. prior to hitting the ground. 'Returns' refer to those peaks which are above a nominated threshold and their coordinates intensity, angle, flight line identification, etc. are of interest to the user (Isenburg (2013)).

The storage format of the LiDAR data is generally binary and vendor-specific. However, the exchange of data among users and across different software applications is traditionally accomplished via its conversion to simple ASCII representations in which every line lists the features of a single return. Although LiDAR returns are flexible and easily understood, the storage of millions or billions of returns in the textual format is bulky: the size of the file expands, data parsing can be wasteful, and seeking within the file is impossible. To addressing these issues a simple binary exchange format was developed by the ASPRS; namely, the LAS format (Samberg (2007)). This is presently the industry standard to store and distribute air and mobile LiDAR data.

Over the last 10 years, LiDAR has emerged as one of the preferred technologies for remote sensing (Liu (2008)). Their active sensor systems utilize a short wavelength laser light to collect precise and dense data on the targeted objects. Achieving the correct range is accomplished via measures of the delay in time between laser pulse transmission and reflection detection. Several LiDAR systems are available to serve different purposes. For instance, airborne LiDAR systems are typically used to acquire spatial data whereby the aircraft- mounted scanner records the earth's topography as illustrated in Figure 2.6.

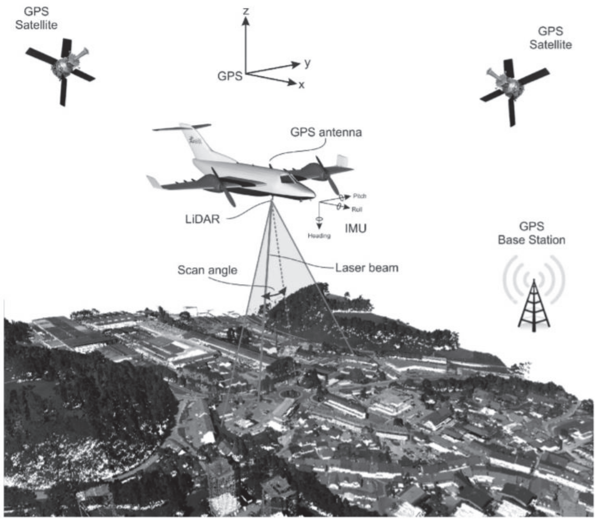


Figure 2.6: LiDAR (Mongus et al. (2011))

Geo-referencing the data is accomplished via the use of a supplementary sensor system. For example, angular orientation is established using an Inertial Measurement Unit (IMU) to measure the aircraft's heading, roll and pitch. An additional measure of the scan angle determines the angular direction of the laser pulse being emitted which then enables the range measurement to be mapped into 3D-point coordinates. Lastly, Global Positioning Systems (GPS) are utilized to determine the LiDAR scanner's position being used to transfer the point coordinates into a local or global system (e.g. the Gauss-Kruger system and Universal Transverse Mercator system, respectively). In addition, several systems utilize digital cameras to capture images of the scanned terrain to collect point colours. Currently, airborne LiDAR systems can execute more than 150,000 measurements every second, with a density of more than 10 points every square metre. Moreover, they can differentiate between diverse reflections from one emitted laser pulse enabling the penetration of cover vegetation to record the terrain below.

Large data-sets are generated however potentially containing multiple millions of points. Open standard binary LAS file formats designed by the American Society for Photo-grammetry and Remote Sensing are typically used to store the data-sets. The LAS format aims to facilitate a standard exchange of the LiDAR data collected.

Notwithstanding that the LAS file format recommends different categories of point record, a minimum of 160 bits per point is applied. As a consequence, LAS files can take up more than a gigabyte of storage every square kilometre. In practical terms, this is problematic, and it is thus not surprising that storage costs, distribution difficulties for users, and the time required to exchange data via the internet have emerged as important LAS data compression issue (Mongus et al. (2011)).

2.10.3 LiDAR Data Compression Techniques using Wavelet

Light Detection and Ranging data compression remains an area of research interest in the 3D data compression field. Regarding lossless compression, the point cloud subject to decompression must have an identical set of points as entered the compressor. Compression is achievable within this constraint, but not to a large degree. Geospatial imagery generally requires a multi-resolution level or scale data storage to access course granular data rapidly. The user typically requires this feature to 'scroll' through large data-sets when performing an 'overview' Upon identifying the feature of interest, users utilize geospatial imagery resolution to 'zoom' into the region for a more detailed image. Such situations generally utilize lossy-based compression.

The possibility to accomplish greater levels of compression in lossy-based compression that do not need absolute precision and accuracy. For instance, the process may be to decrease point precision or even to take out some points while retaining the capability to maintain global surface or elevation features while also minimizing some local changes. The removal of points requires the provision of data related to the point's statistical displacement. Although there have been many advancements in LiDAR data compression methods, the size of the compression remains around a gigabyte. This is not practical for applications used for database data storage and there is an increasing expectation of applications that need semantic data and object approximation to support the fast retrieval of information (Li (2013)).

2.11 Summary

This chapter discussed major issues relating to Digital Data Compression Techniques. Similarly, the core components of the data compression approach and fundamental techniques used in compression were also discussed, including the background of major Data Compression Techniques Algorithms as they are applied in digital imaging. The trade-off between compression performance and quality criteria became apparent. It also presented the process and concepts considered in evaluating the efficiency and effectiveness of compression techniques.

A compression system is robust if it can reduce data size or storage capacity. Image enhancement and image compression form the major steps and basic pre-processing steps in the field of image-based processing. Image enhancement improvises the visual image quality; meanwhile compression of digital images decreases the capacity needed to save images by retaining the same quality as that of the original image (section 1.8). The use of compression techniques helps in reduced hard disk usage. It is a method that employs encoding of an original image with less bit-size. Reduction of bytes is necessary to save digital images, while restoring the image quality. The driving advantage of doing it is one can save a greater amount of images in a reasonable amount of space available. Thereby it also reduces the time consumption to send the images across the internet and helpful in downloading images from the web pages.

The literature review is completed to interpret the differing characteristics and working operation of compression techniques. This research has provided clear knowledge on the field of compression and enhancement techniques, and how it is applicable for medical imagery (section 4.3). Initially our compression method is done using both lossy and lossless compression techniques using Wavelet technology based on HVS. After that, the enhancement method for the compressed images using Histogram Equalization (more details in chapter 4).

This chapter also provides key concepts for evaluating compression capacity and imperceptibility. It showed that the reliable and accurate approach to determine the visual quality of compressed imagery is by subjective-based evaluation approaches. Although, subjective approaches are time dependent, not real-time and costly. Thus, objective evaluation approaches for the assessment of the overall qualities of digital imaging is reliant on mathematical equations that provide faster results.

Descriptions are involved in the existing array representation of multidimensional data and traditional compression schemes for data which include 3D. 3D data compression is a challenging and relevant topic especially for 3D scanner images and 3D LiDAR images where "large" 3D data is processed.

3 Image Data Compression, Methodologies and Associated Mathematical

3.1 Overview

The process of designing "candidate" systems involves the generation of one or more sub-systems that together solve the research problems, as shown in chapter 1. The design of any "candidate" system involves aspects of a literature review, which identifies the purpose and the specification of the research approach. The design includes the low-level components and steps as depicted at Figure 3.1 which also shows the implementation phases of the system and design of an architectural model suffusion for problem solutions.

Figure 3.1: Research methodology flowchart

This research involves a mixed set of different methods as shown at Figure 3.1. It consists of a "quantitative method" which is the investigative approach from an empirical, systematic way where one observes phenomenon through mathematical, computational or statistical ways. A "qualitative method" is composed of unstructured techniques which include items such as: group discussions, individual interviews, and participation/observations, and at least one case study. The quantitative method includes discovering a "data analytic" which is a tool for examining data sets and other tools, databases, along with studying distributions and assessing hypotheses. It also involves simulations using, for example "MATLAB" which is a highly mathematically oriented high performance computer language and the ".NET Framework" which use for software development. In addition, this research involves qualitative data collected from webpages, textual documents, negotiations with other researchers, application developers and empirical experiences on these process and practices; these are combined with results from quantitative studies. In this chapter, section 3.2 to section 3.6, inclusive provides the mathematical basis of the tools used to achieve the research aims and hypothesis.

This research will introduce wavelet transforms in the compression domain. This is a mathematically-based resource that effectively obtains information via various data kinds, inclusive of imagery and audio-based data. The use of the wavelet transform on Human Visual Systems (HVS) in a compression domain will assist in providing high actual information capacity but with minimum storage space. This model manifests how HVS evaluate the compressed image, thereby achieving high compression ratios and enabling images with high visual quality as shown at Figure 3.2, such that there is no obvious differences between original imagery and compressed imagery.

(a) Original image **(b)** Lossy compress image **(c)** Lossless compress image

Figure 3.2: High visual quality results

Nevertheless, such models show a high complexity along with a sub-optimal nature. To achieve the most out of the perceptual model, some global and adaptive search techniques such as using wavelet transformed HVS and other images enhancement using histogram equalization are optimal. In this chapter, HVS is reviewed in context with interactive multimedia data compression. Furthermore, this part also explains Contrast Sensitivity Function (CSF), which defines the limits of the HVS, which may impact on data compression. Some valuable use of image compression such as Noise Visibility Function (NVF) and Just Noticeable Difference (JND) is considered.

3.2 Image Compression Algorithm Techniques

Image compression is a commonly employed approach in image-based processing. The main point of compression of digital imaging is to decrease the amount of data required to symbolize an image by eliminating spectral as well as spatial redundancies. In this research, digitized images are implemented as either medical images and/or photographs, rather than as specific analogue imagery. The data volume required to describe the imagery significantly reduces transmittable rates and increases costs associated with storage as shown at chapter 2 section 2.2. Hence, the information included in the imagery should undertake compression through the extraction of elements that are visible, and encoded afterwards. The data compression is intensified in a substantial way will decrease the data quantity (Kumar & Sonal (2007)).

The goal of compression of imagery is the reduction of capacity of storage or transmission bitrate while providing high-quality imagery and/or sustaining reasonable levels of reliability. Wavelet-based encoding ensures a significance in enhancing the quality of the imagery at compression ratios that are notable. Before, many advanced and sophisticated schemes of wavelets for data compression of imaging are undertaking enhancement. Included on the basis of wavelet is both short support and long support functions. The former is the wavelet's capacity to capture the discontinuities, ruptures and singularities within the dataset for high frequencies. The latter is the wavelet's capacity to detect the data's course structure to determine long-term trends for low frequencies. There are many advantages associated with wavelet-based compression algorithms that are convenient for the new JPEG2000 standards (section 3.2.1 No (2)). Transform-based image compression is a successful application of wavelet methods. By data transforming, one can eliminate redundancies, quantization transforming co-efficients takes place and eventually entropy encoding of the output of the quantizer. The reduction of overall information is delivered by the stage of quantization which specifically discards redundancy of the image information (Salunke et al. (2015)).

Image compression responds to the issue of decreasing redundancy and the irrelevance of imaging data that is capable of storing or transmitting information effectively. As there is potential growth in the medical data, the need for specialist techniques of image compression for storing a large amount of data. Image-based compression lowers the size of an image, but not significantly reducing the image quality overall. Reduction of the size of the data source assists in the storage of a larger amount of imagery, making it easier to send and communicate to other systems (Tummala & Marni (2017)).

Thus, a great number of methods is available to compress images. Image compression can be conducted with or without data loss. Data compression is fundamentally categorized into:

- Lossy Compression and
- Lossless Compression Techniques.

3.2.1 Lossy Compression Algorithm Based On Wavelet

This subsection is focused on algorithmic approaches applied for image compression using wavelets, to measure its performance. The methods are shown as follows:

- Embedded Zerotree Wavelet (EZW) Encoding
- Joint Photographic Expert Group 2000 (JPEG2000)
- Set Partitioning in Hierarchical Trees (SPHT) and
- Highly Scalable Set Partitioning in Hierarchical Trees (HS-SPHT)

1. Embedded Zerotree Wavelet (EZW) Encoding

The algorithm is applicable in demonstrating the overall effectiveness of image compression using wavelets. Embedded Zero-tree Wavelet encoder (EZW) encoder from Shapiro is unavoidable when EZW encoding is investigated in wavelet-based literature for image compression methodologies. The encoder design and specification is implemented with wavelet transforms. The main reason is such that the part of the encoder name includes 'wavelet'. The EZW encoder was working on 2D signals such as images, though it is possible to utilize the encoder on a multi-dimensional basis (Ghahabi & Savoji (2011)).

The EZW encoder compresses imagery in a bitstream that is accurate and precise. That means, that the greater the amount of data is included; a greater level of details shows in the image being decoded. As well, it occurs with the image that is encoded in JPEG. The EZW schema used for encoding along with certain types of optimizations, leading to an effective compression of any graphics limited so that the compressed specification data include desired bit rate. However, information loss will occur, especially in the employment of compression that is lossy. Although, compression that is lossless may happen with EZW encoding, but comparatively lesser results (Sukanya, Y. and Preethi (2013)).

A Discretized Wavelet Transform (DWT) changes the signal from the domain of time into joint time scale. Thus, the coefficients of wavelets are dual dimensions. In in the case of a transformation of signals that are compressed, the encoder is notable for values of the time-based position and coefficient. For imagery being a signal, the time-based point is typically conveyed as a space-based position. Afterwards, the wavelet changes the imagery, the utilization of trees (as discussed at subsections later in this thesis) due to sub-sampling is done in the change (Rehna, V.J. and Kumar (2012)). The co-efficient in a sub-band that is lower, it is observed as having quadruple relatives in greater sub-band (see Figure 3.3).

The EZW encoder improves the zero-tree considering the perceptivity that wavelet coefficients become diminished with scale. It is because the estimator that each coefficient in the quad-tree is short than a specific limit if the root is lesser compared to the edge. Thus, the whole tree can be then coded using solitary-based zero-tree imagery. However, if the imagery is checked-in a predefined manner, high-to-low scale, many positioning is encoded with the utilization of zero-tree imagery. Thus, the zero-tree is cancelled in a frequent manner - though the chances are mostly high as a rule. The cost to pay is the expansion of the zero-tree image to the code letter set (Valens (1999)).

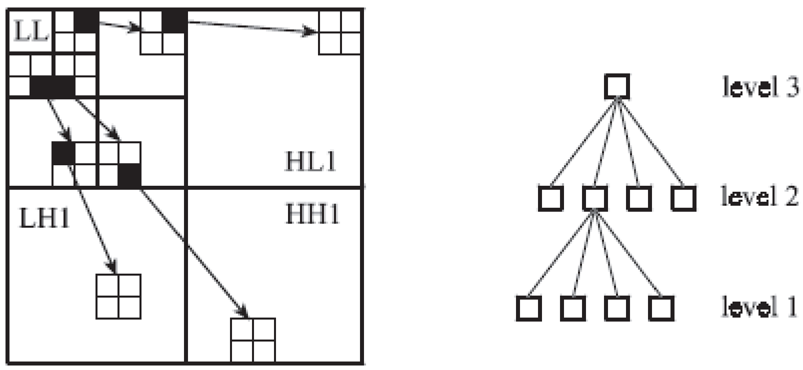
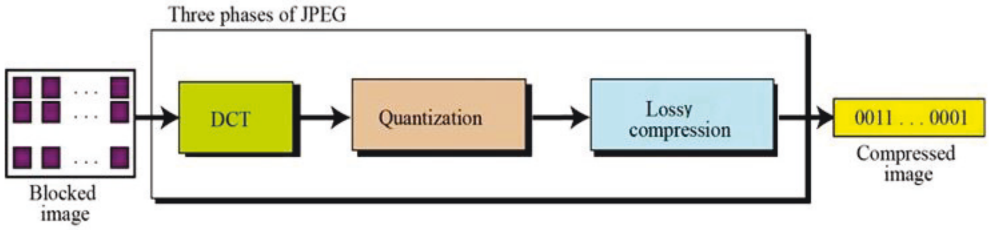


Figure 3.3: The connection with coefficients of wavelets in various sub-bands as quad-trees (Valens (1999))

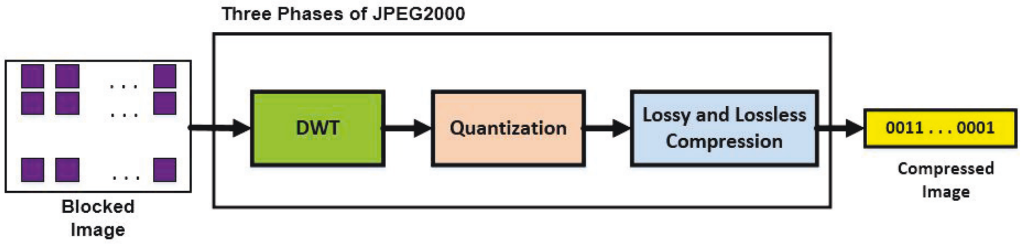
The Algorithm 8.1 provides more detail regarding to EZW coding is available in **Appendix A**.

2. Joint Photographic Expert Group 2000 (JPEG2000)

The standard of wavelet image compression established by the JPEG committee (Joint Photographic Experts Group) was intended to replace JPEG's Discrete Cosine Transform (DCT) with wavelet transform (Wallace (1991)). JPEG itself is a series describe cosine function with some up cosine function for different frequencies commonly related to Discrete Fourier Transform (DFT). Figure 3.4 shows the differences between JPEG and JPEG2000, 3.4a illustrates the division of a grey scale image into blocks of 8×8 pixels, followed by applying a Discrete Cosine Transform and then the quantization table. To cover the limitation of JPEG there is a newer standard of JPEG which is JPEG2000 based on DWT. The goal of JPEG 2000 was to improve performance of compression over that of JPEG, but add/improve features such as editability (ability to edit) and scalability as depicted in 3.4b.



(a) JPEG compression process



(b) JPEG2000 compression process

Figure 3.4: The differences between JPEG and JPEG2000

The objective of the (JPEG2000) is to add to another image compression framework for a vast range of still images (bi-level, greyscale, shading, multi-part) with different qualities (consistent tone, content, therapeutic) for different imaging models (customer/server, transmission in real-time, image library archiving, restricted buffer and transfer speed assets) and ideally inside a uniform framework. The JPEG2000 was proposed as another undertaking in 1996. A call for specialized commitments was made in March 1997. The subsequent compression advancements were assessed in November 1997. Among the 24 calculations, the Wavelet Coded Trellis Quantization (WCTQ) calculation was selected and chosen as the reference JPEG2000 algorithm (Liu et al. (2006)).

Its principle parts are discrete wavelet transformation, trellis coded quantization which it is used in the optimization of residual DCT co-efficients after estimation of motion in a lossy manner, and parallel number juggling bit plane coding. A definite portrayal of this calculation can be found at references (Aboufadel, E., Elzinga, J. and Feenstra (2001)). A rundown of center investigations was performed on this calculation and other assistive strategies as far as the JPEG2000 sought components. They were assessed regarding intricacy and meeting the objectives of JPEG2000. As indicated by the after effects of these trials, a Verification Model (VM), which was a reference programming of the JPEG2000 that was utilized to perform further center examinations. It was redesigned considering the after-effects of the center tests that were examined at each JPEG2000 meeting.

JPEG2000 deals with the basis of Image Tiles. The source imagery is apportioned into rectangularised non-covered abstracts in a process known as tiling. The tiles are made compact in a free manner as if they were autonomous imagery. The operations of entropy encoding and segment blending wavelet transform quantization is done in an autonomous manner on a different tile. The ostensible tile dimensions are multiples of a factor of two, except for the image limits. Tiling helps to decrease memory needs, and as each tile is reproduced in an independent manner, they are utilized to unravel parts of the imagery in a particular way, instead of the whole imagery. Every tile is taken as a numeric variety in sign as an extent representation, then the various bit-planes are depicted. The bit-planes successively are double-based clusters with a piece from a coefficient of the exhibition of the whole number. Primary piece plane encapsulates the Most Significant Byte (MSB) of the size number that is considerable. The second cluster encapsulates the next MSB, proceeding until eventually at the end, comprising the minimum number of bits for a number of sizes (Skodras et al. (2001)).

Initially, the forward discrete wavelet transform (DWT) is tile bound with tile imagery being DC-level altered by subtraction of the equal value, such as the profundity of the segment. Moving the DC level considers the movement of the tile imagery to a coveted piece plane, utilized for the locale of enthusiasm-based coding procedure shown in Figure 3.5.

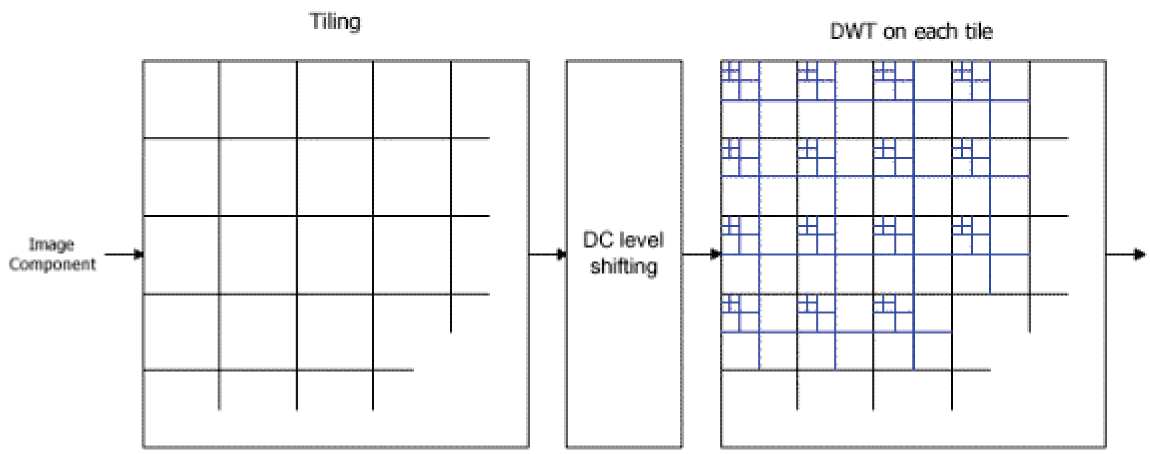


Figure 3.5: Tiling, DC level shifting and DWT on each tile (Aboufadel, E., Elzinga, J. and Feenstra (2001))

This JPEG2000 image compression standard consists of some basic steps in the **Algorithm 8.3** is available in **Appendix A**.

3. Set Partitioning in Hierarchical Trees (SPIHT)

A modern lossless image compression methodology is a Set Partitioning in the progressive calculation as proposed by NirmalRaj (2015) which uses wavelet transforms. The conversion of an image to wavelet transform is achieved using a wavelet-based image compression coder. The fully progressive nature of this algorithm is its primary advantage. The method involves the coding of wavelet transform coefficients and transmission of the bits. The significant among intense wavelet compression is that of Set Partitioning in Hierarchical Trees (SPIHT). The focus of SPIHT is that it produces high image quality with significant PSNR, so it is an approach for dynamic imaging transmission. At the start, the imagery is broken into sub-groups of four. Each sub-groups comprises a single frequency that is a lower sub-band of one, and frequencies that are a higher sub-band of three. The procedure is then rehashed until achieving the last scale (Dudhagara & Patel (2017)). The whole SPIHT algorithm does compression in the following stages, by sort refinement and quantization. SPIHT encodes imagery information as follows:

1. List of Irrelevant Pixels (LIP): Individual coefficients having extents less than threshold values.
2. List of Irrelevant Sets (LIS): General wavelet coefficients in a tree structure, with extents less than threshold values.
3. List of Significant Pixels (LSP): Pixels arrangement having greatness more prominent than the estimated limit of critical pixels (Nagamani, K. and Ananth (2011)).

The algorithm of SPIHT (NirmalRaj (2015)) uses the link between wavelet coefficients existing over DWT imagery sub-bands - between band correlation - and by collecting related coefficients into Spatial Orientation Trees (SOTs), as shown in Figure 3.6. In particular, every coefficient at a determination level, except the most abnormal, are identified with quad coefficients at the following comparable introduction level. Figure 3.6 shows a part of SOTs for the initial gathering of 2×2 pixels in a DWT image with double disintegration levels.

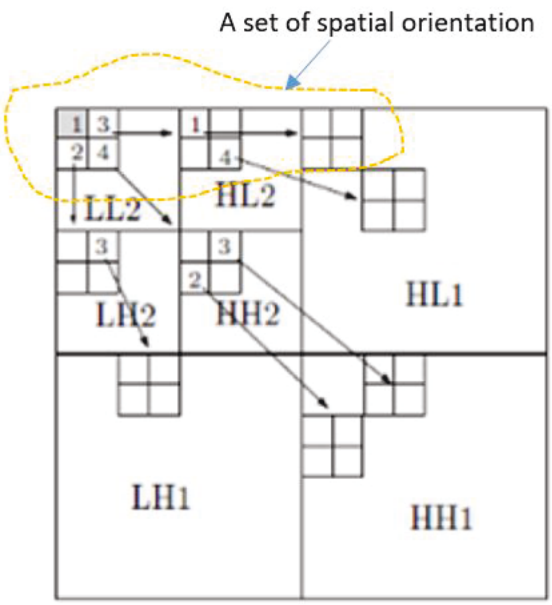


Figure 3.6: Part of the SOTs for a 2-D levels of DWT image (NirmalRaj (2015))

SPIHT compresses in these three steps:

- Sorting
- Refinement and
- Quantization.

The algorithm encodes the imagery sorting into lists including: LIS, LIP and LSP. The LIP process encapsulates single co-efficients with a magnitude less than thresholds. LIS encapsulates whole coefficients of wavelet given in a tree based configuration that has magnitude values less than thresholds. The LSP is a pixel set that has magnitude values larger than pixel values of the threshold with importance. The largest coefficient in the spatial orientation of the tree based structure is represented by n_{max}, and as per (Equation 3.1):

$$n_{max} = [log_2(max_{i,j}|c_{i,j}|)] \tag{3.1}$$

Where $max_{i,j}$ is the maximum magnitude of the coefficients to be encoded and $c_{i,j}$ is the value of coefficient at each coordinate given by (i, j).

In the sort process, all pixels in the LIP list are verified as to their importance and coordinates and pixels with co-efficients in the 3 lists are examined with Equation 3.1. As each coefficient determent to be important and thus removed from the sub-sets, then included into either the LSP or into the LIP dependent on the result of the test. In this process of refinement, MSB of n^{th} sized of the coefficient which is considered as complete outputted entries in LSP. Values of n are reduced, the sorted and refined until $n = 0$. In this manner, the SPIHT algorithm manages the rate of bits precisely and the process and be ended when desired. At the end of the encoding, the process of decoding is done as shown in **Algorithm 8.4** is available in **Appendix A**.

4. Highly Scalable Set Partitioning in Hierarchical Trees (HS-SPIHT)

Highly Scalable SPIHT (HS-SPIHT) algorithm considers issues with spatial adaptability, displaying levels of determination, and pass of categorization that employs an extra summation known as the List of Delayed Insignificant Sets (LDIS). Firstly, HS-SPIHT encodes all piece planes for a specific low determination level, then shifts to an accompanying higher determination level. Sets experienced during the pass of sorting lying beyond the evaluated spatial determination are considered in LDIS. The move from LDIS to LIS when it is required to encode the accompanied higher determination. As accorded to the coefficient number in the wavelet pyramid, greater determination encoding bunches of the signal begins from planes of a lower piece (Polikar (2006)).

Encoding the determination level k, the encoder ensures the coefficients number placed in LDIS for every stage of quantization. In finishing the procedure of encoding for all piece spots of determination level k, such that the encoder recognizes where the entry in LDIS resides to which bitplane. The encoding of the supplemental triple sub bands for the level of resolution $k-1$, it shifts the related LDIS entry belonging to the LIS bitplane, carrying the LIS sort with equivalent tasks as mentioned. Henceforth, the amount of bits in a plane of the piece is equivalent for HS-SPIHT and SPIHT, yet HS-SPIHT appropriates throughout various spatial determination levels (Danyali, H. and Mertins (2002)). The Step of HS-SPIHT encoding shown in the **Algorithm 8.5** is available in **Appendix A**.

3.2.2 Lossless Compression Algorithm Based On Wavelet

This section deals with two of principal algorithms used by lossless method includes:

- Shannon Coding
- Huffman Coding

1. Shannon Coding

This is an early technique of compression, done in 1949 by Robert Fano and Claude Shannon. This technique generates a binary-tree like structure to symbolically represent the probability of each data item. They are organized as the most frequent at the top of the tree and the least likely at the bottom (Shannon (1948)).

The Shannon algorithm is a lossless compression method based on Shannon tree. To form a tree as accorded by Shannon, a table that is ordered is needed to provide the level of frequency for any data item. Each table part is split into dual segmentations as depicted in Figure 3.7. The algorithm ensures that both the up and low part of each segment has a frequency sum that is almost the same. The procedure is looped until one singular data item is remaining. This algorithm works on a few pixels of an image to be compressed, and splits this pixel into two segments thus creating a Shannon tree branch. When dividing the list into two parts, is the total frequency counts of the left hand should be as close to the total of the right is possible. Then assign the left hand of the list a 0 and the right half a 1 as shown in Figure 3.7.

Figure 3.7 above shows the encoding tree of each symbol present in data. Recursively apply steps 6 and 7 (Algorithm 3.1) to the two halves, subdividing groups and adding bits to the code words until each symbol has become a corresponding leaf on the tree (Shannon (1959)).

The Shannon algorithm is an entropy-based encoder algorithm that assigns variable code of length code to characters from the input data stream, writing them to a stream that is output as compressed. Shannon algorithm procedure is as shown at Algorithm 3.1:

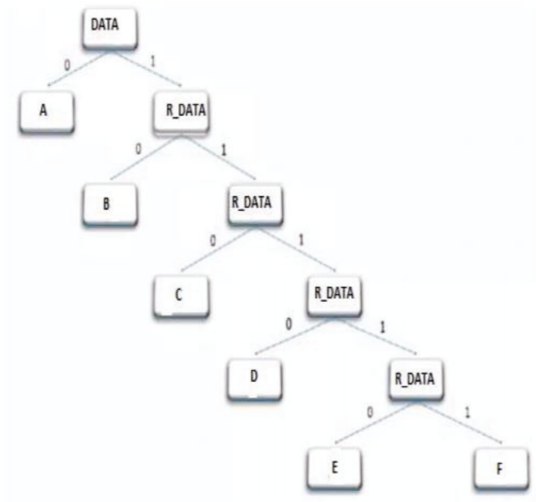


Figure 3.7: Shannon tree coding (Vaidya, M., Walia, E.S. and Gupta (2014))

Algorithm 3.1 Shannon Algorithm

1. Load I = Input images
   O = Output Images
   PN = Parent Node
2. Read I as ASCII Code characters $(c1, c2..ci)$ present in a file with their frequency
3. Arrange the I in descending order according to their frequency$(f1, f2...fi)$
4. Calculate the total Frequency F
5. Selecting Partition PN with all distinct characters to partition
6. From left keep on adding $fi's$ symbol by symbol until sum reaches just above $F/2$
7. Divide the PN into left assign as 0 and right child nodes assign as 1
8. Recursively perform the above step 7 until characters are isolated and occupy leaf node
9. Generating Compressed File with adding bits to the code
10. Get O Result

2. Huffman Coding

In 1952, D. A. Huffman improved a method of a code construction that can be implemented to perform lossless compression. Input data is divided into a sequence of symbols to assist the modeling process. The Huffman method is static, implements a two-pass reading of the data file to be compressed and forms a Huffman tree (Har-Peled (2012)). This approach encodes the symbols with the assistance of a binary tree by joining the lowest two frequencies to establish a code tree. Huffman codes depend on the number of characteristics frequencies that tend to appear frequently. The larger the Huffman code frequency, the lower the bit numbers are formed. Equally, the lower the Huffman code frequency, the higher number of bits are formed during compression (Scribes et al. (1952)).

The Huffman compression algorithm contains methods of lossless compression. Lossless compression as a technique will not modify the initial data to a reduced size. ASCII character represents control characters and alphanumerics in 8 consecutive bits. The rationale of Huffman's algorithm is shown by the following example: a file includes a row of characters "$AABCD$", say, then the number of bits in the file is 40 bits (5×8) or 5 bytes. If each character is given a code $A = 0$, $B = 10$, $C = 111$, $D = 110$, say, then a file of size of 10 bits (0010111110) is required. It is noted that the codes have to be unique, basically that code can't be formulated from alternate codes (Fitriya, L.A., Purboyo, T.W. and Prasasti (2017)). Using the previous example the code criteria is unique and the characters produce a limited by a number of bits of data set for encoding, then the Huffman algorithm can be used to compress, and form the Huffman Tree (Thakral, M.D. and Sandhu (2014)). The example would then be encoded using Algorithm 3.2.

Algorithm 3.2 Huffman Algorithm

1. Load I = Input image
   O = Output Images
   FO = Frequency of Occurrence of Data
   HT = Huffman Tree
   N = Node in the sub-tree
   SN = Sub-Node
   PN = Parent Node
2. Read I as ASCII Code
3. Calculate FO by Type and Amount
4. Sorting on the FO from small to large
5. Formation of the HT
6. Select 2 of lowest F and treat it as the first node of Huffman Tree
7. Create PN from those 2 N and count the sum of their F
then
8. Remove those 2 N and replace with the PN, it will be used to create the T
   while $N \succeq 1$ (more than one node in tree)
      do $N - 1 = SN$ (small sub node)
       for SN
         do code $SN = 1$(only one node left)
       end for
      end while
9. Convert Exciting I with bit code
10. Repeat step 4 but in this time sorting from large to small
11. Every node that place at left branch will be given 0 value and the right branch will be given 1 value
12. Read from the root of the T to all nodes by checking their branch
13. Get O result in bit code

3.3 Data Compression Coding System in the Context of Wavelet Transform

With imaging and sensor technology improvements, image sizes have risen dramatically over the years. For the transmission and storage efficiency of images that are of high-resolution, the images are compressed using a lossy or lossless technique. Generally, this is accomplished using PSNR (Peak Signal to Noise Ratio) or MSE (Mean Squared Error) of distortion that is mathematically tractable in this research. It is noted that because these metrics are inconsiderate about the data's visual importance, visually important details are usually eliminated during the compression phase. Thus, the properties of the HVS must be included in the implementation of the encoding system to yield optimal qualities in visuals (Pandey (2014)). The human eye has variations in sensitivities to different sub-bands (see section 1.4).

Wavelet-based approaches for compressing imaging has been widely employed over time. The wavelet employs sub-band coding to particularly obtain various sub-bands from the digital imagery. Then, the sub-bands can be quantized with other quantizers to yield optimal compression results. The wavelet filters accomplish constraints known as 'smoothness constraints'. The filters are built so coefficients in each sub-band are nearly uncorrelated from other sub-band coefficients. The wavelet transform accomplishes optimal energy compactivity than DCT, hence aiding in better compression for the same PSNR. Much investigation on the performance comparison of DCT and DWT for compression has been done (Kaur & Kaur (2012)).

JPEG2000 has distinct advantages in the way imagery is represented of high resolution. Because of the wavelet transform, JPEG2000 can inherently decode multi-resolution from just one file. In addition, digital imaging with JPEG2000 is then reconstructable with variations in quality, regions of interest along with components according to preferences. This is of particular use when the imagery is remotely accessed via the Internet. One browses the imagery in an interactive manner by only retrieving only a part of the stream of code. This potentially reduces the bandwidth requirement to a significant degree (Chen et al. (2013)).

To use for compressing, the use of wavelet signals is extensive. These are some areas such as imaging of medical subjects where compromised or distorted images cannot be contemplated for obvious reasons. These are utilized to reduce image distortion. For example, wavelets of a scale that is fine can be utilized for effective de-noising (Rao & Latha (2010)).

3.4 HVS Based on Multimedia Data Compression

3.4.1 Background of Human Visual System

The platform of the compression of imagery by Wavelet Transforms, there is the perceptual approach by considering the Human Visual System characteristic in the stage of quantization. Notably, human eyes do not have sensitivity equalization across the bandwidth of frequencies. Thus, the reconstructed image clarity can be optimized by weighting quantization according to a Contrast Sensitivity Function (CSF) . The visual perception at lesser bitrates is minimized (Liu et al. (2006)). In applying the Wavelet Transform on an image, often it provides notable non-zero wavelet coefficients. To obtain a high compression ratio, it is essential to cancel most of the non-zero coefficients without reducing the image quality. To accomplish this, HVS properties can efficiently quantize wavelet coefficients (Yao & Liu (2017)). The HVS has three basic parts:

1. Human eye optical characteristics concerning the sensitivity as relative to the background luminosity and spatio-temporal frequencies. The sensitivity is known as contrast sensitivity, which is elaborated as the contrast sensitivity function.
2. The visual pathway and this ensures a connection between visual cortex and the eye.
3. Elaborates the image formation in the visual cortex. Interactions of neurons in the visual cortex lead to visual masking, as it impacts a visual signal by reducing its visibility in the presence of a different visual signal. This happens between neurons from different (inter) and similar (intra) frequency, colour channels and orientation. These interactions are essentially modelled to convey the effect of visual masking.

In this chapter, reviews how the Human Visual System is applied in multimedia data compression. Additionally, describes Contrast Sensitivity Function (CSF) which is the capacity of the human visual system of multimedia data compression. Some valuable use of image compression such as Just Noticeable Difference (JND) and Noise Visibility Function (NVF) is also analyzed.

3.4.2 Human Visual System Characteristics

Significant enhancements in qualities of the outputs that are processed are achieved as HVS is established in algorithms of compression (Wang Aili Wang Aili, Zhang Ye Zhang Ye (2006)) (Antonini, M., Barlaud, M., Mathieu, P. and Daubechies (1992)) (Hakami, H.A., Alzughaibi, A.D. and Chaczko (2015)). This is done through the optimization of the performance of the compression of images, via taking advantage of limitations in HVS upon the application of compression. There are some limitations regarding visual perception. However, image compression can take advantage of these limitations. Minimized sensitivity for spatially-based high frequency data is a notable downside of the HVS model. One can demonstrate this through the Contrast Sensitivity Function (CSF) (Kammoun, F. and Bouhlel (2005)) (Bradley (1999)). To proceed in this process, it is important to conduct psychophysical observations to appropriately examine the performance of the HVS model. This is strictly conducted due to the complex nature of the HVS system. Physiologists have conducted many experiments in terms of processes that are psycho-visual and awareness of the HVS model.

3.4.3 Human Visual System in Compression Techniques

The Wavelet-based image coding system correlated well with the HVS models. This is associated with the wavelet decomposition properties linked to space frequency localization (Bradley (1999)). The application of HVS model is conducted either at the stage of quantization (Hontsch, I. and Karam (2000)) or through the special codecs stage of bit allocation (Voukelatos & Soraghan (1997)). Therefore, significant improvements are achieved in nearly produced imaging in terms of quality of visuals. A different scheme-based approach for wavelet-based coding depends on image-based compression utilizing the joining of HVS properties and Vector Quantization (VQ) including: texture preference CSF, masking effects and edges created by others methodologies. The vectorised quantization of co-efficients in many sub-bands is achieved via the Discrete Wavelet Transforms (DWT) algorithm. In particular, weight-based Mean Squared Error (MSE) criterion of distortion is implemented as a foundation for allocating bits amongst many sub-bands. This is conducted via a stage of weight identification to be applied, when the HVS modelled is implemented (Campbell, F.W. and Robson (1968)).

Perhaps, another wavelet compression technique is demonstrated in a study at section (2.7). It utilizes both HVS and the VQ concerns by calculating the values of Contrast Sensitivity Function (CSF) specific for the sub-bands' frequencies that is spatial centrally. The values are used in a subsequent manner in the scaled values of sub-band thresholding. Vector selection is done using the values that are obtained, before the process of VQ commences. In a similar way, an application of a distortion criterion of the weighted MSE utilizing weights that are perceptual is accomplished. Basically, this is done by the designation of the bits to a multitude of sub-bands. Significant enhancements are explained by Soraghan and Voukelatos when methods of compression employing blocks are executed at much lowered bitrates (Nadenau et al. (2003)).

3.4.4 Threshold Selection from Human Visual System

The Human Visual System often uses mathematics to model humans' visual perception of the world. It can perform various actions that cannot be done with current technologies. Nonetheless, it has limits when visual perception is concerned. These insignificant imperfections do not inhibit for detection of vision. Although, these limitations may be taken advantage of during compression of images. One important limitation of HVS is the reduced sensitivity for structures of spatial high frequency. This is seen by CSF, or Contrast Sensitivity Function. Moreover, the fundamental characteristics of HVS that are combined into a compressed representation of data when implemented in techniques associated to image compression; i.e: contrast sensitivity and orientation sensitivity (Walker, J.S. and Nguyen (2001)). These HVS characteristics demonstrate human spatial frequency sensitivity. Mannos and Sakrison contemplated a CSF-based model, specifically for greyscale or luminance imagery through Equation 3.2:

$$H(f) = 2.6\,(0.192 + 0.114f)\,e^{\left[-(0.114f)^{1.1}\right]} \tag{3.2}$$

Where $H(f)$ is contrast sensitive function, $f = \sqrt{(f_x^2 + f_y^2)}$ with units of cycles/degree represents spatial frequencies. And f_x represents the frequency of spatial constructs horizontally with f_y vertically.

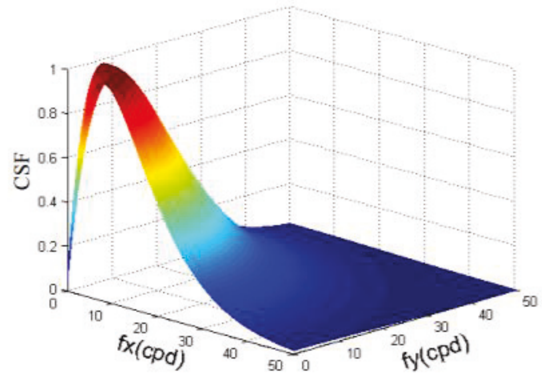


Figure 3.8: 2D CSF curves (Wang, A. and Meng (2012))

Form the Figure 3.8, shows that the information contained in the low- and mid-frequency sub-bands is of greater value than the information contained in the high-frequency sub-bands. This is consistent with the image's distribution of fields. Regarding the transform domain, the distribution of smooth fields occur in low-frequency sub-band; whereas, the distribution of texture information occurs in high-frequency sub-bands. Based on the CSF frequency importance, the process to weigh transform coefficients showing different parameters provides a higher number of bits to domains sensitive to human vision compared to domains which are less sensitive to human vision (Wang, A. and Meng (2012)).

HVS introduces various application in image processing. The first model of HVS was PSNR, which is the performance parameter of image compression HVS further playing a role in maintaining good image quality (Nadenau et al. (2000)). The following functions used for threshold selection from HVS models which are CSF, NVF and JND:

1. Contrast Sensitive Function (CSF)

The function of contrast sensitivity, known as Contrast Sensitivity Function , elaborates the ability of the human visual system to distinguish different luminances "a component of a signal which carries information on images brightness". Researchers have examined the varying contrast sensitivity according to various spatial frequencies (Chung & Legge (2016)), is noted by a stimulus with a structure periodically formed of alternating strips (Kammoun & Bouhlel (2007)). The structure consists of the contrast sensitivity function of the evaluated image in respect to the experimental conditions, the stimulus shape and vision distance. The research has also found the analytic formula that mimic results of the experiment. Widely known is the Mannos and Sakrison formula (Mannos, J. and Sakrison (1974)) it was one of the first and it is used by many studies.

Figure 3.9 depicts a presentation of CSF curve. It shows the luminance sensitivity of the HVS as a function of normalized spatial frequency. The CSF is also a bandpass filter for the HVS and is most sensitive to spatial frequencies between 0.03 and 0.23 hearts (Lin & Jay Kuo (2011)). CSF curves exist for chrominance "it is a colourimetric different between colour in a signal and a standard colour of equal luminance" as well. However, unlike luminance, humans sensitivity to chrominance stimuli is relatively uniform across the spatial frequency.

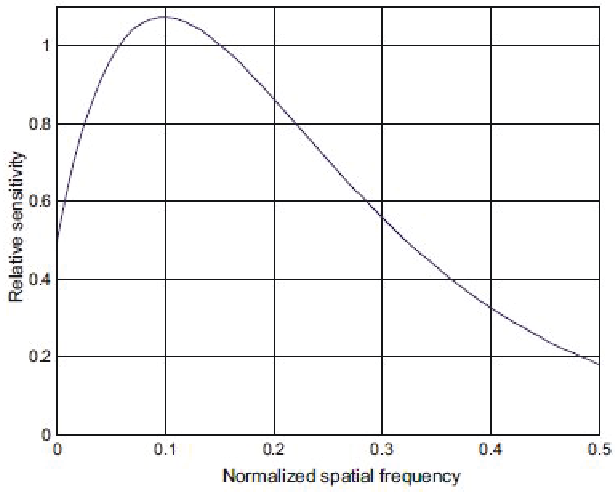


Figure 3.9: Luminance contrast sensitive function (Walker, J.S. and Nguyen (2001))

CSF masking is the name used to refer to the method of weighting the wavelet coefficients relative to their perceptual importance. Figure 3.10 shows the mask of the CSF is done and then inversed in the compression-based platform.

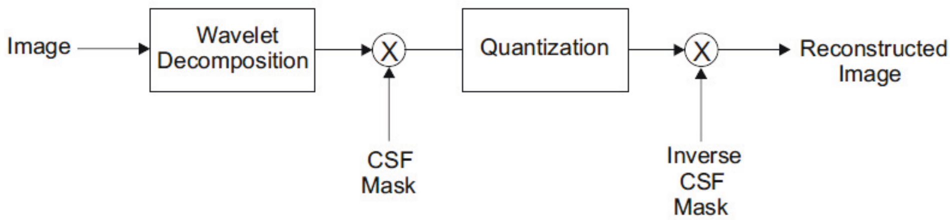


Figure 3.10: Block diagram of CSF masking method (Walker, J.S. and Nguyen (2001))

The ability of a human to distinguish information is linked to the ability to distinguish variations in luminance within a vision field. Luminance changes creates contrast patterns that explains the viewer's visual information. The ability to analyse contrast is impacted by the scene's brightness and intensities of light that is background and ambient. Patterns that are fuzzy, fine or objects that are detailed may need sensitivities to finer contrast grades. Larger objects can deal with lesser sensitivities to contrasting. Within a specific range the abilities to distinguish contrast and contrast changes varies on age and varying factors that are physiological. Humans can distinguish variations on contrast values instead of luminance that is absolute. In a specific set of circumstances for viewing, a slight contrast differential is the thresholding difference in luminance for two zones that is necessary to distinguish the differences. Accuracy of perception depends on object size or pattern, along with the visible time (Johnson & Fairchild (2001)).

2. Noise Visibility Function (NVF)

The Noise Visibility Function is a corrective-based condition that can classify the property of the image for HVS, basing on edges and textures, because data in the region that is embedded can be more compressible with reduced distortion rates. By using NVF for quantization of imagery in the domain of coordinates for prediction schemes, one can be built upon it to the concern of denoising imagery. The common form of empirical-based NVF applications is for applications involving the restoration of images. Furthermore, it is also employed in the selection of thresholds in the decomposition of images. The function of NVF are shown at Equation 3.3:

$$NVF = \frac{1}{1-\theta\delta^2}, \theta = \frac{D}{\delta_{max}} \tag{3.3}$$

Where $\theta = \frac{D}{max[\delta_x^2]}$

$\delta^2 x(i,j)$ is localized variance of imagery in size $n \times n$, being 256 by 256 centred in (i,j).

θ links with adjustment of image-based contrast.

$max[\delta_x^2]$ is localized variance maximum and $D\epsilon[50, 100]$ are parameters.

3. Just Noticeable Difference (JND)

The JND, or Visual Just Noticeable Difference , describes the threshold-based visibility at its minimum when visualized content of the algorithm is modified by transforming the wavelet, resulting from psychophysical and physiological phenomena in the human-based visual system. JND facilitates in the compression of imagery and video streams, evaluation of the quality and watermarking features. The JND values are estimable for domains of pixels sub-bands, or wavelet sub-bands (such as DWT, DCT) (Wan et al. (2017)).

The human visual system can only perceive the changes in pixel greater than a particular threshold of visibility, determined by the baseline psychophysical and physiological mechanism. Thus, not only the statistical properties of the pixels be under consideration, but the features of perception in the processing of images - as HVS is the underlying receiver of most images being processed. JND basically accounts for the maximal distortion of senses that a usual HVS is unable to perceive (for example, 75% of observers approximately) and can be employed in perceptual video and image process algorithms and platforms. JND is the equivalent size as the imagery and the values are estimable for the domain of pixels, or sub-band of wavelet (being the Discrete Cosine Transformable) domain. As two imagery are not observably distinguishable if differences in each imagery for (JND pixel domain) or sub band of image for (JND sub-band) is inside the value of JND. In the compression of video and imagery, JND can be employed to optimize the allocation of bits and eliminate redundancy in perception (Liu et al. (2010)).

JND, or difference threshold, is the minimum difference in stimulation that humans detect 50 percent in an evaluation. It is the largest difference of images which HVS does not allow, used for threshold selection for image decomposition and compression process-it is the function of de-noise image (Ramadhan et al. (2017)). MATLAB "prefers the software median for testing the theory of this research" has a built-in function for JND based on Equation 3.4:

$$[BW,]\, thr = edge\,(x) \tag{3.4}$$

3.5 Image Enhancement Techniques

Image enhancement is considerable as a vital technique the research into imagery. The primary main aim of enhancing imagery is improving the visual quality and appearance of imagery, and/or offer an optimal transformed representative for automatic processing of imagery. Images, especially that of medical subjects, satellite sources, aerial photography and real-life photography would be compromised from low contrast and noise that is high. It is required to improve contrast in order to reduce noise to optimize the quality of the image. An important stage in the detection of medical imagery and its analysis is the use of IET, or Image Enhancement Technique. The image clarity is improved for perception by humans, reducing noise and blur, raising contrast and thus can show details that are useful. To optimize the quality of imagery and enable the inputting for image processing, the following IET can be applied:

1. Spatially-based domain methodology: The process undertakes directly on the digital-image's pixels, leading to enhancement of contrast.
2. Frequency-based domain methodology: The process undertakes on the transformation of the Fourier function of the digital-image.

3.5.1 Spatial Domain Methods

Minimal execution is necessary for the spatially-based domain methodology, requiring reduced time for computation (Song & Woo (2015)). It is achieved by applying Equation 3.5:

$$g(x, y) = T\,[f(x, y)] \tag{3.5}$$

Where

$f(x, y)$ refers to imaging taken as inputted,

$g(x, y)$ refers to imaging taken as outputted,

T refers to the operator, described as f applicable over a point of neighbour (x, y).

Using this approach, noise reduction occurs through the application of this operator to the pixel of the digital image or image set. Spatially-based processing factors intensity-based transformative functionality by applying Equation 3.6:

$$S = T(r) \tag{3.6}$$

Pixel-based element (r) maps via pixel-based element (s), using transformative element T. Intensity-based transform takes in three transform types used for enhancement of images:

- Liner negative transforms
- Logarithmic log transforms
- Power low intensity transforms

Transform functions are optimal and taken to be the easiest and simplest methods to undertake. Functions (r) and (s) represent pixel elements before and after processing of the image.

3.5.2 Frequency Domain Methods

Frequency domain methods are the methods that modify the Fourier transform. Then, alter the transform by multiplying it with a filter transfer function. An inverse transform is applied to obtain the modified image. The key is the filter transfer function which includes low pass filter, high pass filter and the Butterworth filter (Shaikh (2016)).

The enhanced image is produced by simply computing the Fourier transform of the image to be enhanced, multiplying its result by a filter (rather than convolve in the spatial domain), and then applying an inverse transform. Blurring an image by reducing its high frequency components or sharpening an image by increasing the magnitude of its high frequency components is intuitively easy to understand. However, computationally, it is often more efficient to implement these operations as convolutions by small spatial filters in the spatial domain (Sinha (2009)).

Low pass filtering involves the elimination of high frequency components in the image. It results in blurring the image and thus a reduction in sharp transitions often associated with noise. An ideal low pass filter would retain all the low frequency components, and eliminate all high frequency components. However, ideal filters suffer from two problems: blurring and ringing. These are caused by the shape of an associated spatial domain filter, which has many undulations (Satpathy et al. (2010)).

Smoother transitions in the frequency domain filter, such as the Butterworth filter, achieve much better results (Sinha (2009)). Images normally consist of light reflected from objects. The basic nature of the image $f(x, y)$ may be characterized by two components: the amount of source light incident on the scene being viewed and the amount of light reflected by the objects in the scene. These are called the illumination and reflectance components and are denoted by $i(x, y)$ and $r(x, y)$, respectively. The functions i and r combine multiplicatively to yield the image function $f(x, y)$ as depicted at Equation 3.7:

$$f\left(x,y\right)=i\left(x,y\right)r\left(x,y\right) \tag{3.7}$$

Thus $0 < i(x, y) < \infty$ and $0 < r(x, y) < 1$.

Homomorphic filtering is applied to separately enhance these components in frequency domain (Abbas, A.P.A.H. and Harbi (2017)). A high pass filter is used to sharpen an image. The process occurs in the frequency domain via a weakening the low frequency or low intensity transition. The output generated via high pass filter techniques includes high intensity transition into a specific assembly of pixels. Image processing for colour image enhancement is also achieved in frequency domain. The following techniques of image enhancements in frequency domain include:

(a) Low pass filtering or smoothing domain filters.

(b) High pass filtering or sharpening domain filters.

(c) Homomorphic filtering (not consider at all) and.

(d) Colour image enhancement.

3.6 Image Compression Enhancement

It is essentially optimizing the perceptiveness or interpretation of information in imaging and offering improved inputs for automatic imaging processors. It is necessary to enhance the contrast and remove the noise to increase image quality. The main driver of enhancing images is adjusting imaging attribute data so it is suited to a task given, along with an observer specifically (Aggarwal & Himanshu (2010)). During this process, one or more attributes of the image are modified.

The choice of attributes and the way they are modified are specific to a given data compression task. Observer specific factors, such as the human visual system and the observer's experience, will introduce a great deal of subjectivity into the choice of image enhancement methods (Karunya (2015)). Image enhancement aims to improve the data in imaging for humanity, or to provide improved inputs for automatic image processors.

Enhancing imaging deals with improving the image quality for better vision. It is defined as the impression of its merit of excellence, as perceived by an observer. Three basic parameters that control the quality of an image include:

- **Contrast:** Refers to the differences in the object's colour and brightness with the colour and brightness of other objects in the same view.
- **Brightness:** Refers to visual perception attributes related to the light reflecting or radiating from the source.
- **Sharpness:** Refers to the focus and contrast clarity of the image; a sharp image subject in typically clear and lifelike as a result of the highly detailed contrast and texture features.

Image enhancement is popular and the most widely known technique of image processing.

Many images such as medical, satellite, aerial and even real-life photography suffer from noise and poor contrast. Image enhancement algorithms offer a wide variety of approaches for modifying images to achieve visually acceptable images. The choice of such techniques is a function of the specific task, image content, observer characteristics, and viewing conditions. The point processing methods are most primitive, yet essential image processing operations and are used primarily for contrast enhancement. Enhancement techniques improve the quality of the image view, blurring, noise and increasing contrast and improve the borders and sharpness of the image. The methodologies are categorized generally as follows:

- **Frequency domain:** Refers to the initial transference process of the image in the frequency-based domains. The Fourier Transformation of the imaging is initially calculated. Next, the transform of the imaging undertakes enhancement processes; before conducting the Inverse Fourier transform to achieve the final image.
- **Spatial domain:** Spatial domain-based image enhancement operates directly on pixels.

Spatial domain and frequency domain include techniques like point processing, image smoothing, edge detection and image sharpening. The techniques used by this research is the spatial domain, which deals with image pixels and enhances the contrast of the compressed medical images. Other techniques used in research to enhance compressed medical images include:

• **Adaptive Histogram Equalization (AHE):** Refers to the computer image processing method applied to enhance the contrast in the image. AHE has been designed in such a way as to be widely applicable and effective.

• **Morphological Operations (MO):** Refers to the method of image processing which relies on the object's shape and form. MO methods rely on the application of a structuring component to the input image, to generate an output image of the identical size (Sreedhar, K. and Panlal (2012)).

It is often necessary to enhance the contrast and remove noise, to increase image quality. One of the most important stages in medical images detection and analysis is IET which improves the quality or clarity of images for human viewing, removing blurring and noise, increasing the contrast, and revealing necessary details (Thakral, M.D. and Sandhu (2014)).

Any survey perhaps of available techniques are based on the existing techniques of image enhancement, which can be classified into two broad categories.

Spatial and frequency based domain image enhancement and Frequency based domain image enhancement. The main advantage of spatial based domain technique is that it is conceptually simple to understand and the complexity of it is low which favours real time implementations. But lacks in providing adequate robustness and imperceptibility requirements (Chauhan et al. (2018)).

Frequency-based domain image enhancement is describing the analysis of mathematical functions of signals with respect to frequency, and operate directly on the transform coefficients of the image, such as the Fourier-Transform (FT), Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) (Singh & Mittal (2014)).

3.6.1 Histogram Equalization

Histogram Equalization (HE) is a contrast enhancement technique in a spatial domain, done by image processing using an image histogram. Histogram equalization increases the global contrast of the processing image to more or less. The method is useful for both background and foreground that are bright or dark for the image (Gaddam, P.C.S.K. and Sunkara (2016)).

Considering the discrete greyscale input Image $X = x(i, j)$, with L discrete levels, and $x(i, j)$ is the imaging intensity levels at the spatial domain (i, j), with the histogram of image X is $H(x)$ and the probability density function $pdf(X)$ is shown at Equation 3.8:

$$pdf(X_k) = \frac{nk}{N} where, 0 \leq k \leq (L - 1) \tag{3.8}$$

Where

L refers to maximal of greylevels in imaging,

N refers to maximal pixels in imaging,

nk refers to maximal pixels with equivalence in intensity level k.

From the $pdf(X)(1)$ the cumulative distribution function $cdf(Xi)$ is defined as:

$$cdf(Xi) = \sum_{i=0}^{K} p(X_i) \tag{3.9}$$

Note that $cdf(X_i)$ from Equation 3.8 and Equation 3.9.

Histogram equalization is a scheme that maps the input image into the entire dynamic range $[X_0, X_{L-1}]$ by using the cumulative distribution function as a transform function. Define the transform function $f(X)$ using cumulative distribution function $cdf(X_i)$ as

$$f(X) = X_0 + (X_{L-1} - X_0) \times cdf(X_i) \tag{3.10}$$

Then the output image of histogram equalization, $Y = y(i, j)$ can be expressed as

$$Y = f(X) \tag{3.11}$$

$$Y = \{f(x(i, j)) \mid \forall x(i, j) \in X\} \tag{3.12}$$

Equation 3.8 to Equation 3.12, inclusive describes the histogram equalization on a greyscale image can also be used on colour images by applying the same method separately to the Red, Green and Blue Components of the RGB colour image.

3.6.2 Enhancement using the Contrast Method

Contrast enhancement techniques are commonly used in various applications where the subjective quality of the image is very important. The objective of image enhancement is to improve the visual quality of the image depending on its application (Bora (2017)). Contrast is an important factor for any individual estimate of image quality. Is often used as a controlling tool for documenting and presenting information collected during the processing for the digital image. Contrast enhancement of images refers to the amount of colour or grey differentiation that exists between the various features in the digital images. Simply, it is the range of the brightness present in an image. Images having a higher contrast level usually display more colour or greyscale differences as compared to images of lower contrast levels. Contrast enhancement is a process that allows image features to show up more visibly by making best use of the colour/grey presented on the display devices (Sharma & Mandavgane (2017)).

From early 2000, several contrast enhancement algorithms have been developed for enhancing images in various applications such as medical image processing, object tracking, speech recognition, give optimum viewing of bone-based structures in x-rays, as well as enhancing photographic details in backgrounds and foregrounds which can be both bright or both dark (Mahajan, S. and Dogra (2015)). Histogram equalization, global histogram equalization, local histogram equalization, adaptive histogram equalization and contrast limited adaptive histogram equalization, other histogram equalization based algorithms and other contrast enhancement methods have been proposed by various researchers (R Dorothy , RM Joany , R Joseph Rathish , S Santhana Prabha (2015)). One of the most widely used algorithms is global histogram equalization, the basic idea of which to adjust the intensity histogram to approximate a uniform distribution. It treats all regions of the image equally may yield poor local performance in terms of detail preservation of image (Singh, K. and Awasthi (2013)).

Histogram equalization is a technique that generates a grey-map which changes the histogram of an image and redistributes all pixel values to be as close as possible to the user-specified, desired histogram. This technique is useful for processing images that have little contrast with an equal number of pixels to each of the output grey-levels. The histogram equalization is a method to obtain a unique input to output contrast transfer function, based on the histogram of the input image which results in a contrast transfer curve that stretches the peaks of the histogram (where more information is present) and compresses the troughs of the histogram (where less information is present) (Das et al. (2015)).

3.6.3 Enhancement using the Brightness Method

To preserve brightness, a code is applied in accordance with a setting a limit to preserve brightness. At the end of the entire process, an image obtained is contrast enhanced, brightness preserved as well as there is a natural look to the image. This distinguishes the method from others (Nimkar et al. (2013)).

3.6.4 Enhancement using the Noise Removal Method

Noise is the most common problem which is present within any image. Noise in an image is induced during image acquisition, image, due to the noisy sensor and due to corrupted storage media. In digital image processing, to removed undesired grey-level variations, i.e., noises from an image, low-pass filtering are generally employed. Low-pass filters have been developed for de-noising, that include: simple Gaussian filters (Wrangsjo et al. (2003)), Yaroslavsky neighborhood filters (Yaroslavsky (1985)), bilateral filters (Tomasi & Manduchi (1998)), non-local mean filters (Buades, A., Coll, B. and Morel (2005)), anisotropic diffusion filters (Perona, P. and Malik (1990)) (Barash (2002)), median-based filters (Poularikas (1999)). Each filter has its own merits and demerits depending on its application. Some filters are more efficient in removing noise while blurring the image, whereas others a capable of moderate noise removal with good preservation of signal clarity (Li et al. (2017)). Hence, the computational complexity of each filter is different (Nahar (2012)).

Two techniques which are commonly applied to raise contrast in imaging are linear digitization, along with non-linear digitization as present in Figure 3.11. The linear method is sometimes referred to as contrast stretching and involves the linear expansion and new distribution of the original digital values assigned to the remotely sensed data. The process to expand the image's original input values enables the use of the full sensitivity range of the display device. Subtle variations in the data can also be made pronounced using linear contrast enhancement. The nonlinear method of contrast enhancement generally includes the application of an algorithm to achieve histogram equalization. The main disadvantage of the nonlinear contrast stretch technique is that each single value in the input image can end up having multiple values in the output image. As a result, the relative brightness value of the objects in the image may not be correct in relation to the original image (Al-amri, S.S., Kalyankar, N.V. and Khamitkar (2010)).

Median based filters are non-linear filters, which have a good quality of preservation of signal variations during noise smoothing, even if the signal variations and the noise occupy the same frequency band. These filters are based on order statistics (Cannistraci et al. (2015)). A basic square median filter arranges all pixels of a small window in sequential order, and replaces the center pixel with the middle value of the ordered set.

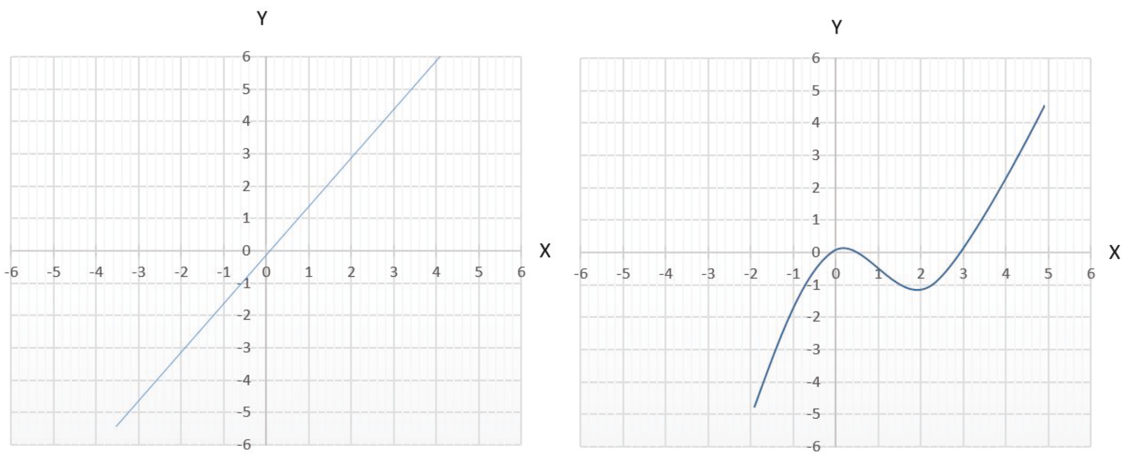


Figure 3.11: Linear and nonlinear digital techniques

Since the replaced values consist of one of those present in the neighborhood, unlike the average filters, it is more efficient to preserve the signal variations. Also, as it does not introduce any unrealistic values during the filtering process and it can be used repeatedly to strengthen noise smoothing. However, there are some demerits of square median filters: they cannot preserve the corners of the image objects and may also erase thin lines within image itself. To overcome the problems of square median filters, many advanced median-based filters have been developed, including: weighted median filters, median hybrid filters, multi-stage median filters (Nahar (2012)).

One of the aims of the work in this thesis is the effective removal of noise from a compressed enhanced image with preservation of signal variations.

3.7 Wavelet based on Image Enhancement Techniques

Wavelets play a major role in image compression and image enhancement to represent the image signals into an order of increasing resolutions (Shivani Jain & M.Tech (2014)). Since a major topic of interest by this research is image enhancement, its discussed in more details in chapter 4.

Wavelet coefficients calculated by a wavelet transform represent a change in the time series at a specific resolution. By considering the time series at various resolutions, it is then possible to filter out noise as shown in more details at chapter 4. Wavelet transform is a powerful tool for filtering which represents images hierarchically based on scale and resolution. It analyzes high-spatial frequency phenomena localized in space and thus it can effectively extract information derived from localized high-frequency signals such as those emitted by micro-calcification clusters when performing mammograms the important of that classification cluster of cancer (Moradmand et al. (2012)).

The genericized form for a 1D or one-dimension wavelet transformation is observed in Figure 3.12. In here, signaling is carried in low (H) and high (G) pass filtration, sampled down by a factorization of 2 that constitutes a single transform level. Multitude scales of the wavelet transformation are done by looping the decimation and filtration process on branched low-pass outputs. Hence, such a process is run for a limited level number (K), with the resultant co-efficients being wavelet-based co-efficients (Al-Samaraie (2014)) as calculated by Equation 3.13:

$$d_{i1}(n), i^{\epsilon}\{1, ..., K\} \; and \; d_{k0}(n) \tag{3.13}$$

In Figure 3.12, the output of half is determined by filtration of input $H(z)$ and downsampling by a factorization of 2; the remaining output is determined by filtration of input $G(z)$, and then downsampling by a factorization of 2. $H(z)$ is a low-pass along with $G(z)$ being high-pass filtration. The single dimension wavelet transformation is extendable to a dual dimension wavelet transformation utilizing wavelet filtration that is separate. Separable filtration of 2D transforms are calculated by employing a 1D transformation to the input rows, and then to the columns afterwards. The imaging of Lena in Figure 3.13 provides a sample of a 1-level 2D wavelet transformation ($K = 1$). An example is looped for 5-level wavelet expansionism ($K = 5$) as observed in Figure 3.15 (Shivani Jain & M.Tech (2014)).

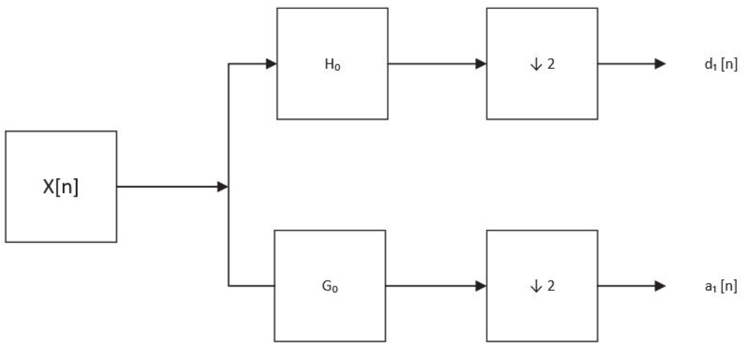


Figure 3.12: One level wavelet decomposition tree

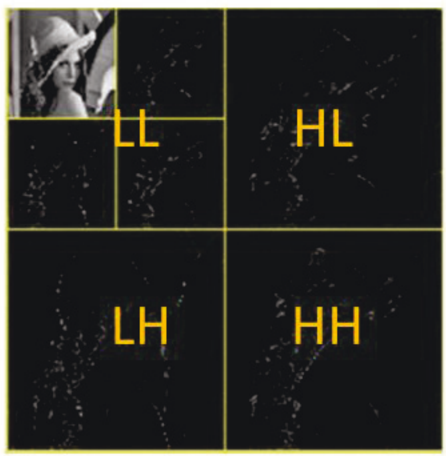


Figure 3.13: Two level wavelet example (Singh & Khare (2013))

Figure 3.13 shows that sub-band LL has greater importance than three depicted sub-bands, representing a coarser equivalent of the source imaging. Multi-resolution feature of wavelet transformation have led the popular usage for image enhancement.

The Figure 3.12, shows signaling sequencing $x[n]$, n being an integer; H_0 is high-pass filtration and G_0 is low-pass filtration. For the levels, high-pass filtration gives information in detail $d[n]$, though low-pass filtration linked with scale function gives a coarser approximate $a[n]$. De-composition is looped to raise resolution of frequency and approximated co-efficients is de-composed from high and low-pass filtration and sampled down seen in Figure 3.14. Hence, it is representative as a binary de-composition tree, the nodes are a subspace with varying localization in time frequencies - tree refers to the bank of filtration.

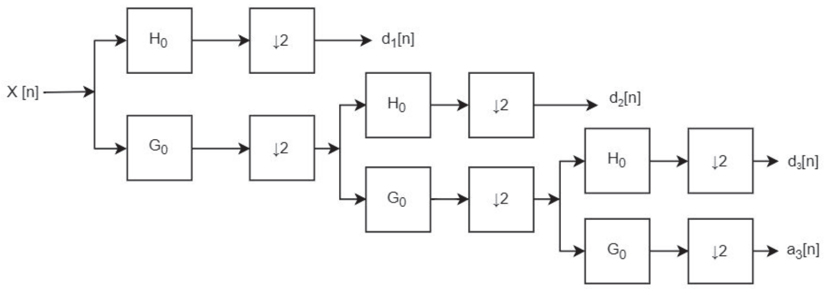


Figure 3.14: Three- level wavelet decomposition tree (Rajput et al. (2012))

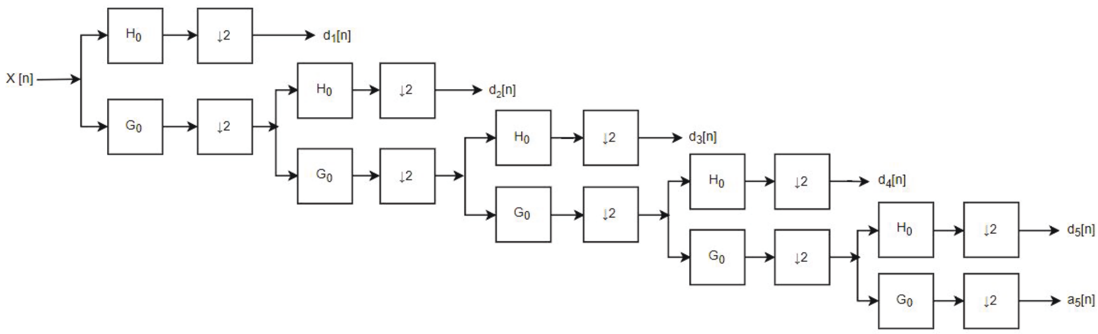


Figure 3.15: Five- level wavelet decomposition tree

3.8 Summary

This chapter presented a summation of the properties of the human visual system. The work shows a system dependent on key applications of wavelet transforms to compress images. In addition, it also reviews efficient image quality metrics in terms of Human Visual System (HVS) and its associated features. Furthermore, it also investigates how the eye of humans does not really possess a greyscale error sensitivity. However, certain sensitivities are recognized by regarding image edge properties.

Image Enhancement algorithms offer a wide variety of approaches for modifying images to achieve visually acceptable images (acceptable loss), by choosing techniques which are a function of specific tasks, image content, observer characteristics and viewing conditions. It also includes an overview of Image Enhancement Processing Techniques in Spatial Domain.

To summarize, the chapter includes an overview of the human visual system characteristics that depend on the details of wavelets filtering and the implementation of the human visual system. Furthermore, the features of Human Visual System (HVS) have been reviewed.

4 Data Compression Experimentation

4.1 Overview

Data compression is an active research area in computer science focusing on deriving techniques, or more specifically, designing efficient algorithms: to solve and represent data in a less redundant fashion; removing redundancy in data; and the implementation of the algorithm in code, including both encoding and decoding of data. Recently, the main research area has been in multimedia computing. This has led to varying applications including video, image and graphical data. Moreover, data compression is notably useful in communications as it enables digital systems to transmit and store information more efficiently.

There are many distinctive techniques to compress and decompress images in the field of digital processing. Each of these techniques has different output results and implementation approaches. Among many of those techniques, the JPEG2000 compression standard is utilized, since it has the capacity to compress a lot of information into the smallest possible size when compared with the actual image size. The imaging compression performance procedures are enhanced by installing a system supported by the Human Visual System (HVS) section (4.3).

The Human Visual System (HVS) compression-based model calculation offers a significant change in the visual nature of the reproduced image; the execution of imaging compression methods are fundamentally enhanced by taking advantage of the restrictions of HVS for the purposes of compression. HVS is a system of data processing that yields better quality of images as a whole. At a basic level, an image data item could be considered as structures made up of surfaces of the same shading or a composition limited only by edges.

In this chapter present, the experimental result for data compression algorithms and image enhancement techniques to analyze the performance parameters after reducing the data size using compression techniques with the Human Visual System (HVS). From the results and analysis of these data compression methods are effectively optimized to accomplish the goal of the research.

4.2 Computational Framework for Lossy Data Compression using 5-D Multi Wavelets Transform

4.2.1 The Problem

This chapter presents the results of the experiment to test the research hypothesis reported in Chapter 1. Emphasis is on the following characteristics while validating the research hypothesis:

- **Compression Ratio:** One of the characteristics that make the compression algorithm flexible is the compression ratio (Aguilera (2007)). It is described being the ratio of bits in an originating source to the bits in number used to represent the compression output.
- **Storage Capability:** Image compressing aims to reduce the space needed for the storage of digital images. The use of digital images is common to many fields and there is sometimes the need to compress the images for certain applications. The technique applied for image compression will depend on the application requirements. The goal when compressing an image is to reduce, as much as possible, the total bit number while maintaining, to the best of the ability, the reconstructed image's visual-based quality as compared to the original image (Khobragade & Thakare (2014)).
- **Perceptual Quality:** Perceptual evaluation of quality has many applications in practice. It dives a primary concern in influencing most processing systems and algorithms that are visually based, including testing, implementation and optimization.
- **Image Quality:** Measurement of quality of imaging helps to drive applications for imaging processors, the aim being the methods of IQA or Image-based Quality Assessments to automate the evaluation of imaging quality alongside judgments in quality for a human audience (Lin & Jay Kuo (2011)).

By utilizing techniques for image compression that emulate the human visual system (HVS), the compression considers the significance of every individual coefficient of the image. A portion of high compression ratio is normally achieved by forcefully exploiting the set limitation of the HVS system section (2.6.2). Psycho-visual research has demonstrated that HVS has diminished sensitivity with high spatial frequencies (Astle et al. (2010)). The function has been enabled by the state-of-the-art contrast sensitivity function (CSF) technique. Properly utilizing this function can altogether enhance the compression function without acquiring recognizable changes in the quality of the image.

Wavelet Transform technology enables image compression by the use of Human Visual System (HVS) attributes in the stage of quantization section (3.4.3) (Hakami, H.A., Alzughaibi, A.D. and Chaczko (2015)). Human perception lacks the sufficient level of sensitivity throughout the visualized bandwidth completely. The clearness of reproduced imaging are enhanced by quantization weighting as indicated by CSF, also known as the Contrast-based Sensitive Function. When a wavelet change is applied to an image, its often provides an excess of non-zero wavelet coefficients. In order to be able to have capacity to achieve high compression ratios, it is important to attempt to uproot most of the non-zero coefficients without destroying the final image quality. To achieve this, HVS properties are utilized to effectively quantize wavelet coefficients.

4.2.2 Proposed Method (LCT-HVS)

The research factors compression as a potential key to reduce the time to store, retrieve and transmit information. This research strikes a balance in the image quality, compression ratio and processing time with the Human Visual System (HVS). The optimum compressable methodology for the converting of multimedia is converting at the highest ratio while minimizing distortion. Thus, the proposed method using 5-D multi-wavelet transform is using HVS with JPEG2000 encoding, to accomplish better image quality, a high compression ratio and fast, real-time execution. The experimental task has optimized the compression performance and compared with other previous methods; it has accomplished the optimum result of compressability using the 5-D multi-wavelet based on HVS.

Lossy Compression Techniques (LCT) built on the Human Visual System (HVS) model has been incorporated with the JPEG2000 encoding approach as shown subsequently. The technique that has been proposed is able to: provide adequate quality, along with a compression ratio of significance and reduces compression time. The use of the technique to perform compression considers multiple stages as depicted in Figure 4.1.

The technique shown at Figure 4.1 start off by loading an uncompressed image and converting it into compressed images. Then the image is processed by a 5D multi-based wavelet, following with entropy and quantization-based encoding processes. Next, selecting level-dependent thresholding value is done via JND, HVS, NVF and CSF, then calculation of performance parameters in real time is done progressively. Reconstruction of the imagery employing 5-D wavelet requires notable prepositional steps which analyses the resultant compressed imagery. The key driver is adopting the optimal formatting for the images being compressed.

This is LCT-HVS proposed method that incorporates the following activity:

Step 1: Pre-processing an Uncompressed Images:

- In this step is about selecting the best fit format, analyzing image to determine the size of image, colour, image noise and the notable degree of overall human perceptual quality.

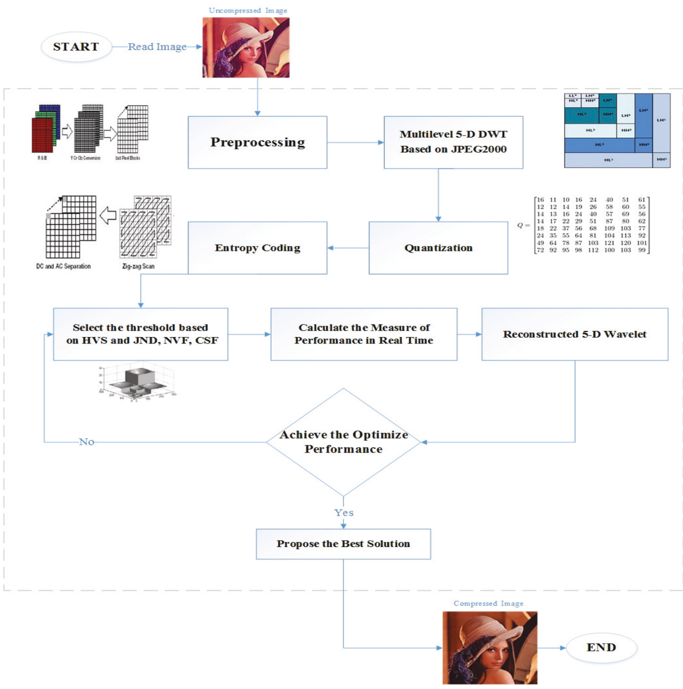


Figure 4.1: LCT-HVS proposed method flowchart

- To compress a colour image the processing begins by converting the Red, Green and Blue colour channels to Y, Cb and Cr colour spaces, and what can be done by a greyscaled image is accomplished to the Y, Cb andCr channels.
- After that, the imagery is divided into squares of 8×8 pixels in size. Then, an additional process is necessary to check the size of the image is not beyond 8 pixels. For the purpose of this research, an image is selected so that its measurements do not exceed $215 \times 384 = 8 * 64 \times 8 * 48$ pixels. i.e; $64 \times 48 = 3,072$ blocks of 8×8 pixels. Figure 4.2 demonstrates that 8×8 pixels blocks.
- Finally, initially the image is prepared by subtracting $8th$ bits from every image pixel force in the block. It is about the focus on the intensity for quality 0, in order to encapsulate the mathematical steps of transforming and quantization.

Step 2: Multilevel 5D Discrete Wavelet Transform based on JPEG2000:

- A wavelet Transform provides a minimalistic multi-determination image representation. It calculates an optimized compaction proposal to suit redundancies in imagery for the purposes of compression. A Discrete Wavelet Transform (DWT) employing a 5D wavelet filter-based bank is applied recursively.
- The input image is initially filtered by lower and higher pass decay-based filtering. Resultant image is filtered in sub inspected in the vertical plane for information in the low and high frequency. The output that is filtered is verified in a horizontal manner and then the channel values are linked in an

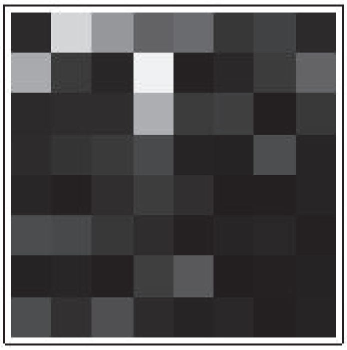


Figure 4.2: Enlargement of the example block

independent manner to generate sub band frequencies that are distinctive. After steps of verifying, store the differences (i.e. residuals) between the imagery and predicted imagery as it transitions from level to level, also eliminating redundant information.

- After data is analyzed in the direction that is horizontal, the gradual transformation outputs produces LL, LH, HL, and HH; every component is approximately a quarter of complete size of imagery that is original (3.7).
- From the process stage, majority of energy connected to sub bands of lower frequency levels. LL is the low resolution equivalent of the source imagery; while sub-bands with frequency that is higher feature image information that is more detailed in horizontal and vertical properties.
- Afterwards for a single transformation stage, imagery is decomposed by the re-application of 5D DWT, to existent LL sub-band as a comparison approach.
- Repetitive approach leads in a number of transformative level outputs that is compacting to a minimal low frequency co-efficients. Figure 4.3 shows the 5D level of JPEG2000 format that is wavelet-based from lower-level LL to the higher-level HH.

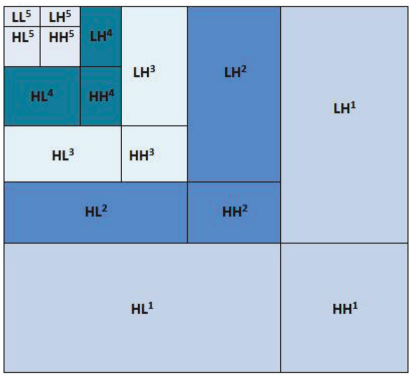


Figure 4.3: 5-D level of wavelet based JPEG2000

Step 3: Quantization Step:

- Quantization is applied to input image values around origin that has a larger set to value outputs has a small set. For an equivalent quantization type, the size of quantization is applied for each image's magnitude. The estimate and quantization size is linked to the image's nature; so if the strip size is smaller, the image's nature increases and vice versa. The default of step size is usually 1.
- After the quantization algorithm is assigned, image bit-data is provided to each sub-based band - the location making plan is straightforward, as it uses 3 spatially steady sub bands of a determination that is particular factoring the area of the segment.
- The frame of packets make compressing optimal in terms of persistence capability. The sorting of the segmented bundle offers a medium, grain-level in the bitstream's area. Square of the code is found by division of segmented area of parcels in oblong tiling.
- Coding is required, which is entropy coding (section 2.5.1).

Step 4: Entropy Coding:

- It is conducted for each square of code. Each block of code contains binary and arithmetic coding. Bit-planes start at the MSB, so encode process starts at the MSB. Then it is applied by a multiple of 3 on every piece plane.
- Choosing a square of code relies on criticality of the neighboring bits, along with the plane area's piece that is present. Area is critical if observed as 1 in code for the area of presentation.
- Main entropy coding pass is known as the engendering pass. Pass asserts code-blocks that the presentation area isn't large, but fewer than 1 of 8 areas of presentation linked with the image bit's notable neighbour. Secondly, the pass relating to the bits of the image with a critical zone, and thirdly is the clean pass dealing with remaining bits that didn't code in the previous passes.
- All code passes are accomplished double numerical connection subordinates to be a flexible and optimal coding, also referred to MQ-Coder as present at Figure 4.4. The driver of QM-based coder is the classification of input bits as MPS or More Probable Symbol (MPS) and Less Probable Symbol (LPS). Prior to the input of the following bit; the QM-based coder makes predictions as to which bit (0 or 1) is classified as the MPS using a statistical model (generally a two-dimensional context comprising of the image with white and black picture elements). If there is a mismatch between the predicted MPS bit and the actual bit, the QM-coder then classifies it as LPS; or else it maintains its MPS classification. The coder's output is a compressed representation of the MPS or LPS sequences, which are given dynamic probability values. The decoder only knows whether the following predicted bit is classified as MPS

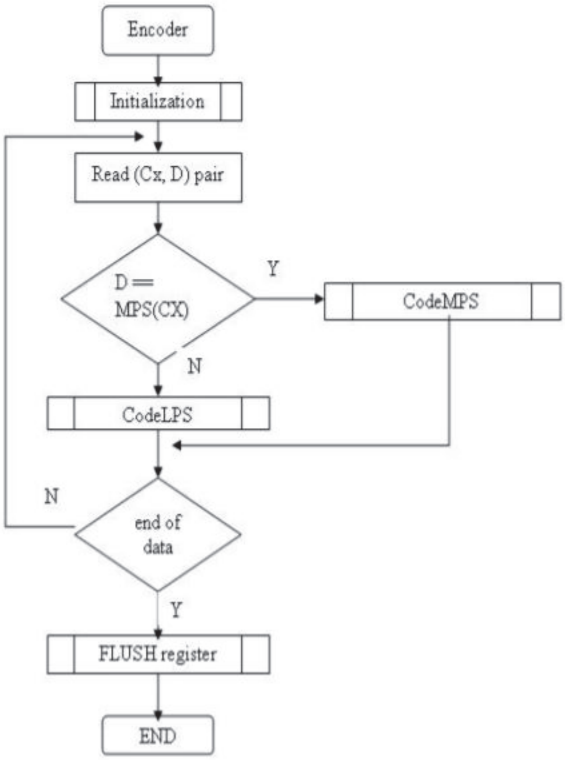


Figure 4.4: MQ-Coder structure chart (Kolluru (2009))

or LPS. A statistical model identical to the encoder is used to determine the bit's actual values (Kolluru (2009)).

- The process is described by the Contrast-based Function of Sensitivity, or CSF (Nadenau et al. (2003)).

Step 5: Selecting thresholds based on HVS and CSF, JND, NVF, :

Principle concerns of HVS are coordinated into representative, packed-based data when utilized in the system and nominated for image-based compression (Walker, J.S. and Nguyen (2001)). The properties of HVS deal with the human's sensitivity of frequency. Mannos and Sakrison suggest a CSF-based model, in particular luminance (greyscale) imagery by offering the helper Equation 4.1 as follows:

$$H(f) = 2.6\,(0.192 + 0.114f)\,e^{\left[-(0.114f)^{1.1}\right]} \tag{4.1}$$

For the equation as stated, $f = (f2x + f2y) \times 0.5$, the cycle/degree-based units describe frequencies that are spatial. Fy describe the direction vertically, while, Fx

describe frequencies that are spatial in the direction horizontally. Normalization of the spatial frequency is done as follows:

$$f\,(cycles/degree) = f_n\,(cycles/pixels)\,.f_s\,(pixels/degree) \tag{4.2}$$

- Thus, the threshold selection is underpinned on the HVS platform. As the original image, the edge of Just Noticeable Difference (JND) reveals its tangible base quality of sign for HVS; with a fit model of JND adequately uprooting perceptual excesses while enhancing the computation of calculating perceptual code. Assisting in demonstrating the model of JND that is proposed, then it is applied to image compression for excess perceptual-based decrements and thus the model of JND assists in qualities of perception that is optimal. An optimal JND-based model has the ability to lead greater noise in specific areas and lesser in locales that are noise-free. Additionally, the JND process is also a threshold of difference, as it is the difference in base to be noticeable for a human eye to ascertain correctly by 50%. Hence, this is the greatest difference in range that is not permissible by HVS, given a selection of threshold. To precisely decide the edge of perception for every coefficient the JND is computed as:

$$JND(k) = \begin{cases} T_0[1-(k/127)^{0.5}]+3 & k \leq 127 \\ \gamma(k-127)+3 & otherwise \end{cases} \tag{4.3}$$

Where

$T_0$and γ describe the distance viewed from the screen at luminance-value with background that is higher.

$T_0$and γ are 17 and 3 /12 additives necessary for the perceived change, being the JND, with the constant being k.

- In particular, the NVF (Noise-based Visibility Function), thus function of the visibility of noise is generated:

$$NVF(i,j) = \frac{1}{1+\theta\delta_x^2(i,j)} \tag{4.4}$$

Where $\theta = \frac{D}{max[\delta_x^2]}$

$\delta^2 x(i,j)$ describe the image's variance that is local, in a window being the size of $n \times n$, for the case being 256 by 256 with the centre (i,j).

θ describe the image's contrast-based adjustment.

$max[\delta_x^2]$ describe the variance at the local maximum, with $D\epsilon[50,100]$ being the parameters as determined.

Step 6: Calculates the Measure of Performance in Real Time:

- This calculates the compression performance of the image-source, including that of SSIM; PSNR; CR or MSE.
- Thus, employment of the JPEG2000 wavelet coefficients, it provides quality that is sufficient, when the PSNR is encoded to the image.

Step 7: Image Reconstruction with 5D Wavelet-based Process:

- The process of re-construction is inverse of the process of de-composition. It involves up-sampling by two of the detail-coefficients and approximation at every level, and transitions through synthetic filtering (low- and high- passes) before being added. Identically, the levels of numbers are applied in the stage of reconstruction as in the stage of decomposition to determine the signal that is original. Described process continues until end.
- During this step, the filters facilitate the formation of multi wavelets which contain the useful wavelet attributes including symmetry and orthogonality. It also provides flexibility in the reconstruction of the image.
- This process relies on the average number of high frequency elements around the absent blocks. In addition, there is the assumption that all low frequency elements are found.

Step 8: Achieve the Optimum Performance:

- In this step, examinations are made of the original and compressed image data to determine if factors of size, quality and time taken to display output is achieved.
- The work will propose the result of this step being the optimal solution available. Instead, repeat the training (going to step 4 again).
- Else, proposed the best solution for these compressed images.

Algorithm 4.1 explains the functional process of methodology being presented.

Algorithm 4.1 LCT-HVS proposed method

1: Start
2: Input Image A, $[r,c]=$ size (A)
3: Output: A_c' (Compressed A)
4: Convert the image from RGB to Y, Cb, Cr
5: Apply Wavelet Transform: $y[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k]$, $W=$ 5 db (Wavelet) to the images
6: Divide the image into blocks
    Do quantization
7: While $k = 1 : 3$ Do Select Methods Using HVS, K (Number of elements in array)
        If $K == 1$ Select NVF then
            Else If $K == 2$ Select JND then
            Else If $K == 3$ Select CSF
        End If
  End While
8: Calculate $|P|$ which is performance parameters
        If $|P| < N$ (N = Best Result) then
            Do repeat encoding step then
                Else If $|P| \geq N$
        End If
9: Display A_c' (output)

4.2.3 Experimental Results

The Algorithm 4.1 (LCT-HVS) is implemented in a successful manner with 1030+ images in colour employing the MATLAB algorithmic implementation. The section present the analyses of a random 6 images from the 1030 colour images which utilizes the Uncompressed Colour Image Dataset (Stich, M. and Schaefer (2004)). The outcome of utilizing Algorithm 4.1 on the 6 random images shows optimum outputs considering high-quality PSNR and good compression-based ratio. The section will also evaluate:

1. Compression Ratio (CR)
2. Mean Square Error (MSE),
3. Peak Signal to Noise Ratio (PSNR)
4. Compression Time (CT) and
5. Structural Similarity (SSIM).

Algorithm 4.1 provides several benefits including good quality (which is above 60% of PSNR and SSIM nearly to 1), high compression ratio (which is above 50%) and reduced processing time (which is below of optimum value). Figure 4.5 provides the original-based source and the image being compressed with LCT-HVS with an optimal PSNR value (60% and above), and compression ratio (50% and above) that is high.

(a) Size of original image: 109 KB, Value of PSNR: 54.2905

(b) Size of compressed image: 36.9 KB, Value of PSNR: 70.0917

Figure 4.5: Image of the original source and compressed result using LCT-HVS methodology

Figure 4.7 provides the six original image sources and associated images that are compressed utilizing five various methodologies. Instead of different methods of compression, the technique being proposed offers colour images that are compressed. Basing on the compression approaches of JPEG2000, EZW, HS-SPIHT and SPIHT, observations are made that the JPEG2000 approach offers optimal performance including high qualities (50% and above), lesser final size of compression (60% and below) and high ratio of compression (40% and above), observed in Figure 4.6.

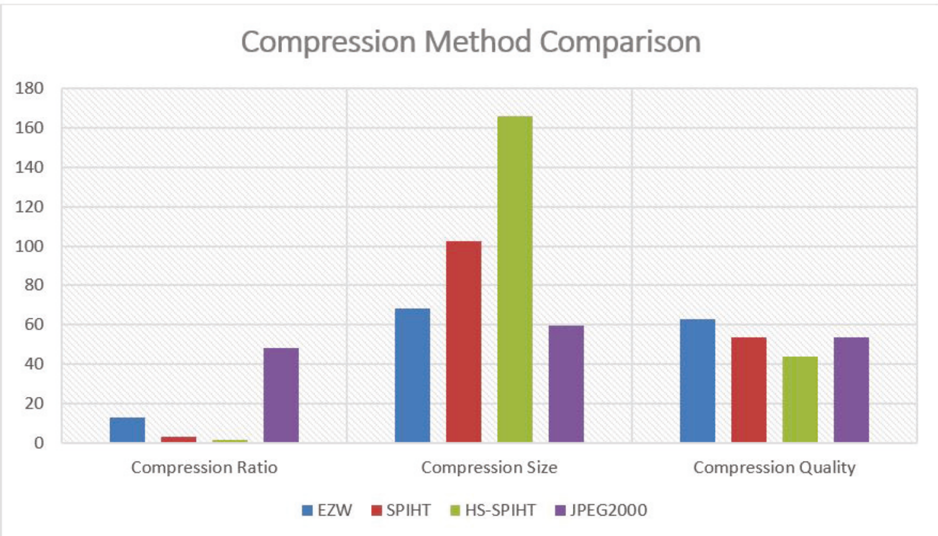


Figure 4.6: Comparison of compression methods

Thus, the exercise adopted the JPEG2000 methodology, linked with the human visual system and wavelets. Table 4.1 and Table 4.2 it shows the comparison of quality and performance between the 5 methods for models of compression for images using UCID, or Un-compressed Colour Image-based Dataset. Whereas, Figure 4.8 presents the assessment of performance-based parametrics for the five various methodologies. LCT-HVS approach minimizes the data size and required time to compress image, in order for evaluation of the quality of image and maintaining the ratio values greater than other approaches. Evaluating the overall utility for every parameters of performance parameters for the five methodologies of compression is shown in Figure 4.8 the LCT-HVS method provides higher quality (which is above 60% of PSNR, SSIM nearly to 1 and the maximum value of MSE is 1). The relationship of the balance between the performance parameter, the proposed methods provide a higher compression ratio (above 50%) with lower compression size (below 50%). Also, the proposed method doesn't take a long time for compression to be evaluated (approximately less than 1 sec per image in our test).

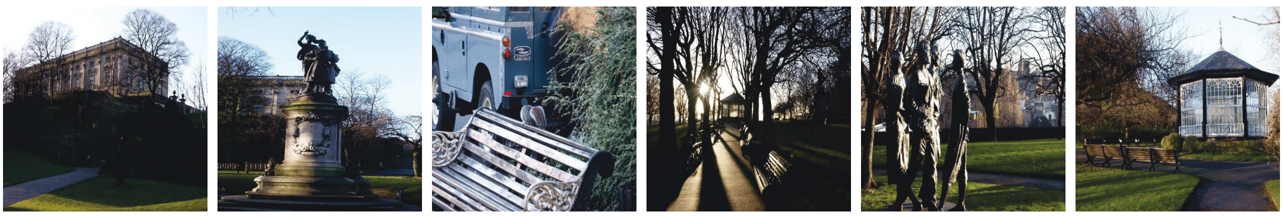
(a) Reference an uncompressed image

(b) The compressed-images with EZW methodology

(c) The compressed-images with SPIHT methodology

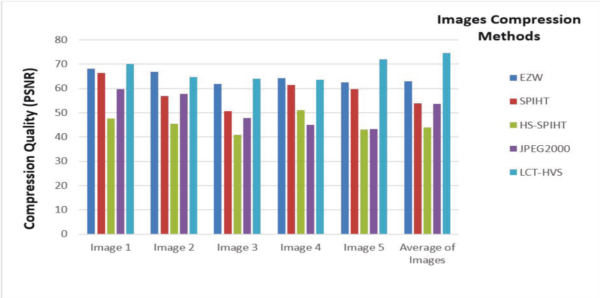
(d) The compressed-images with HS-SPIHT methodology

(e) The compressed-images with JPEG2000 methodology

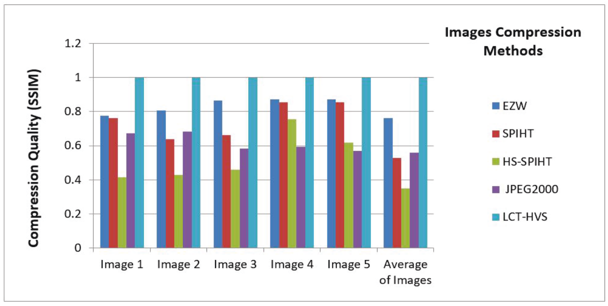


(f) The compressed-images with LCT-HVS methodology

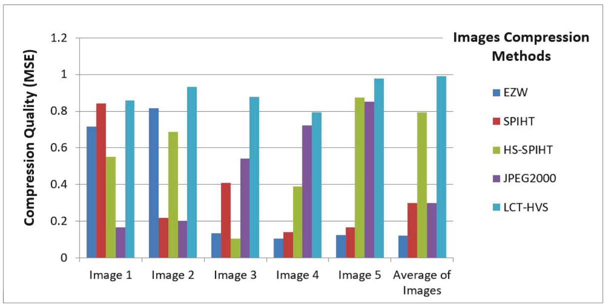
Figure 4.7: References for methods of image-based compression with dataset of UCID



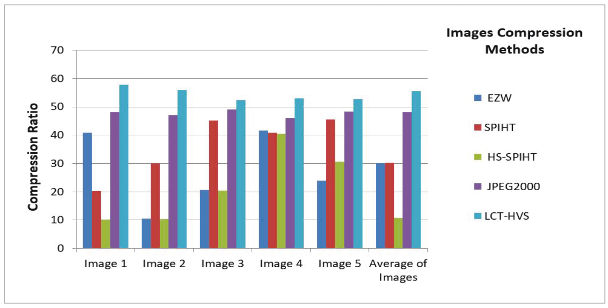
Compression Quality (PSNR)



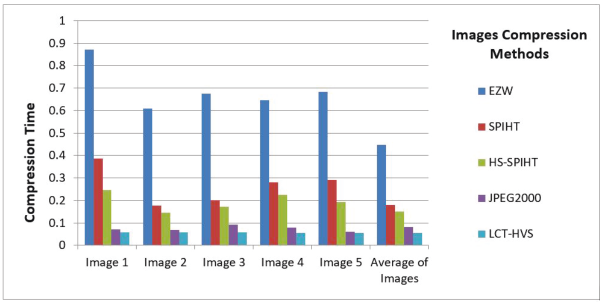
Compression Quality (SSIM)



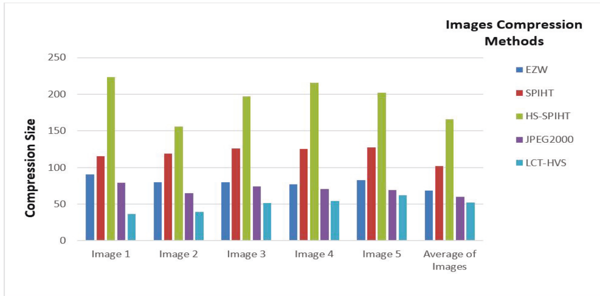
Compression Quality (MSE)



Compression Ratio (CR)



Compression Time (CT)



Compression Size (CS)

Figure 4.8: Evaluation of performance parameters for methods within Lossy-based domains

(a) Comparison of compression quality (PSNR)

Compression Quality (PSNR) Evaluation for Various Lossy Methods					
Images	EZW	SPIHT	HS-SPIHT	JPEG2000	LCT-HVS
1	68.12	66.50	47.71	59.74	70.09
2	66.80	56.95	45.48	57.71	64.70
3	61.82	50.65	41.01	47.88	64.12
4	64.27	61.35	51.14	44.99	63.57
5	62.47	59.71	43.09	43.35	71.90
Average of Images	62.85	53.85	44.09	53.75	74.66

(b) Comparison of compression quality (SSIM)

Compression Quality (SSIM) Evaluation for Various Lossy Methods					
Images	EZW	SPIHT	HS-SPIHT	JPEG2000	LCT-HVS
1	0.7753	0.7650	0.4156	0.6743	0.99994
2	0.8085	0.6378	0.4298	0.6834	0.99976
3	0.0865	0.6631	0.4602	0.5920	0.99989
4	0.8731	0.8555	0.7537	0.5687	0.99946
5	0.8716	0.8535	0.6175	0.5687	0.99981
Average of Images	0.7604	0.5271	0.3490	0.5579	0.99943

(c) Comparison of compression quality (MSE)

Compression Quality (MSE) Evaluation for Various Lossy Methods					
Images	EZW	SPIHT	HS-SPIHT	JPEG2000	LCT-HVS
1	0.7152	0.8412	0.5504	0.1653	0.85899
2	0.8161	0.2184	0.6884	0.2025	0.93355
3	0.1342	0.4103	0.1059	0.5411	0.87821
4	0.1051	0.1408	0.3906	0.7229	0.79663
5	0.1258	0.1658	0.8742	0.8519	0.97663
Average of Images	0.1210	0.2981	0.7944	0.3008	0.98969

Table 4.1: Compression quality comparison for various methods

(a) Comparison of compression ratio

Compression Ratio (%) Evaluation for Various Lossy Methods					
Images	EZW	SPIHT	HS-SPIHT	JPEG2000	LCT-HVS
1	40.964	20.242	10.255	48.152	57.81
2	10.467	30.059	10.458	47.080	55.95
3	20.658	45.175	20.481	50.961	52.39
4	41.624	40.907	40.518	50.142	53.06
5	24.020	45.535	45.535	48.366	52.84
Average of Images	30.052	30.349	30.349	48.223	55.56

(b) Comparison of compression time

Compression Time (Seconds) Evaluation for Various Lossy Methods					
Images	EZW	SPIHT	HS-SPIHT	JPEG2000	LCT-HVS
1	0.8707	0.3864	0.2465	0.0709	0.05863
2	0.6097	0.1765	0.1462	0.0699	0.05691
3	0.6754	0.2008	0.1709	0.0929	0.05725
4	0.6456	0.2794	0.2249	0.0798	0.05587
5	0.6829	0.2904	0.1945	0.0615	0.05603
Average of Images	0.4478	0.1791	0.1519	0.0811	0.0555

(c) Comparison of compression size

Compression Size (KB) Evaluation for Various Lossy Methods					
Images	EZW	SPIHT	HS-SPIHT	JPEG2000	LCT-HVS
1	90.80	115.5	223.4	79.50	36.54
2	79.70	118.8	155.9	65.10	39.60
3	80.10	126.2	197.3	73.90	51.70
4	77.10	125.1	215.7	70.70	54.69
5	82.70	127.8	202.1	69.20	62.08
Average of Images	68.40	102.2	165.7	59.70	52.31

Table 4.2: Performance comparison for various methods

4.3 Computational Framework for Lossless Data Compression using 5-D Multi Wavelet Transform

4.3.1 The Problem

As previous work (section 4.1) shown that with lossy compression technique using 5D wavelet based on HVS and there is information lost from compressed images. For that reason a lossless compression technique using 5D wavelet based on HVS with Reversible Colour Transformation (RCT) to have the compressed images as original images is tried.

With the increasing technologies and rise of the digitized era, one must handle increasing information capacities that presents issues. Hence, digital-based data must be retrieved and stored efficiently for practical purposes. Thus, wavelets can mathematically encode the data so that it is layer-based on the detail level. Layer-based approaches can deal with approximates at varying stages of intermediaries. The approximates are saved with reduced storage than the originating source. It is possible that the originating source where no information loss is necessary; hence techniques of compression that are lossless can be improved.

For a lossless visualized approach, images that are highly compressible face artifacts that are visible. Reducing the level of artifacts mean that the algorithms of compression take advantage of the various sensitivities of the HVS or Human Visual System to differences in frequency, usually obtainable at close to threshold levels where one can perceive noticeable distortion. Moreover, the lossless compression technique converts an input RGB colour images into YUV colour spacing model by the Reversible Colour Transformation (RCT). Luminance component element Y encoding is done by any of the greyscale lossless image coders such as CALIC and JPEG-LS; also the chrominance image component UV are accomplished with pixel-based prediction and hierarchical-based decomposition.

The differences between lossy and lossless means that the lossy based on HVS is no longer viable for the higher demands of processing lossless data. Also, lossless algorithms are typically utilized when the application requires the original data to be reconstructed exactly; whereas lossy compression is utilized when there is an allowance for some distortion by losing some of information.

For the world of today, imaging is a main influence in applications of many kinds. Imaging processors deal with great concerns because digital image data can result in large volumes of data; e.g. High Definition (HD) images on the mobile phone as sent by attachment in an email it takes space, on other hand there is some application can reduce the size with keeping the quality. Recently, to meet types of real-time applications of data compression, for Joint Photographic Experts Group

(JPEG2000), the techniques of compression are employed to reduce the disk space expenditure and bandwidth requirements.

Therefore, lossless compression methods requires an optimized algorithm to be able to effectively compress imaging with minimal information loss. The JPEG2000 standardization consists of lossless and lossy techniques of compression with various modalities of operation. Generally, the JPEG feature is a practical lossy-based methodology recognized as the base-line scheme for other Discrete Cosine Transform (DCT) based ways of action. The cost of transmission for JPEG compressing techniques is great and information is lost in the process. JPEG2000 is a loss-less approach that can be bit-preserved and referred globally for decoding and encoding purposes (section 3.2.1 No.2). JPEG2000 data layout offers a platform for the accumulation of exacting applications associated with JPEG2000 steam of code, especially for information required for imaging presentation. An inverted colour transformation, the reversible colour transform (RCT), is utilized in JPEG2000 with wavelets, providing a math-based approach for encoding digital-image data in a layered approach by taking advantage of the Human Visual System (HVS) in the quantization stage.

The research pursues the aim of lossless-based imaging compression by decreasing the number of bits necessary for computer systems such as storage and transmission of images without any perceptible loss of information. Lossless colour image compression for an image in the RGB colour model is done by a Reversible Colour Transformation (RCT). RCT converts RGB to the YUV colour model; where the Y component is encoded by a method called Lifting Wavelet Transform (LWT) which utilizies the Huffman coding. Lifting-based transform is a technique for undertaking a Discrete Wavelet Transform (DWT) and designing wavelets. One must merge the steps and design within wavelet filters, while also performing a wavelet transform. Any overall signal variation is suppressed by the colour transform and any prediction error is reduced in the chrominance channel. The proposed method used for hierarchical scheme is a way to structure the chrominance image for encoding. Under this process, the chrominance image is decomposed by an even row and odd row image as shown at Figure 4.9 the RCT flowchart. The decomposed image is compressed using arithmetic coding and decoded (section 2.5.1) get the original image, by a reverse colour transformation. Afterwards the image can be reconstructed and performance measurements may be calculated.

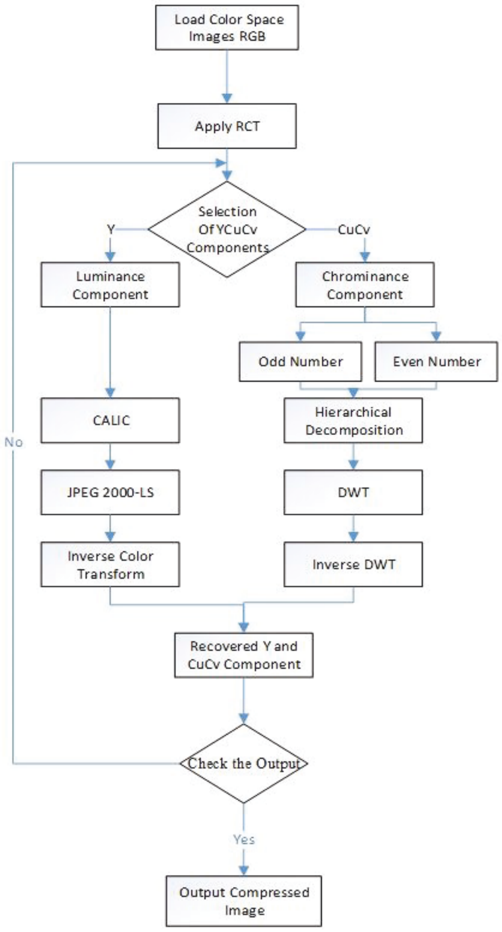


Figure 4.9: RCT flowchart

The human visual system (HVS) drives the quality of the images being compressed ultimately. Therefore, it is necessary to allow designers of systems and end users to harness existing understanding about image quality and models in a system of compression. JPEG2000, a standard of compression based on wavelets, is employed for encoding various imaging such as geospatial images, natural images and medical images as it has improved compression-based performance compared to JPEG standardization. For JPEG2000, a discretised wavelet transformation (DWT) breaks down every component into a multitude of sub-bands having various orientations and frequencies. The proposed visual method of lossless is a motivation for ensuring an image that is compressed is equal to the originating source, while minimizing time of compression (Bhuvaneshwari, G. and Balaji (2015)). Hence, a low-level complex imaging compression methodology utilizing wavelets as basis function is employed, with the goal of measuring qualities of the image being compressed image is the result. The 5D DWT (step 2 in section 4.1.2) is applied and detailed matrices from the imaging matrix are estimable. The image being reconstructed is synthesized using estimate detail matrices; the matrix of information offered by the transformed wavelet. The compressed imaging quality is assessed with factors like Peak Signal-to-Noise Ratio (PSNR) typical might include good quality between 60 and 80 dB, Mean Square Error (MSE) the values closer to 0 are better, Structural Similarity (SSIM) include the maximum value is 1, Compression Size (CS) a good value in lossless compression no more than 45% and Compression Ratio (CR) a higher value in lossless compression 30%.

4.3.2 Proposed Method (LRCCT-HVS)

Lossless Reversible Colour Compression Technique (LRCCT) is a method using Reversible Colour Technique (RCT), basing on the Human Visualized System (HVS) that is applied and implemented to various image types, inclusive of medical and general sources. The images that are used in the test are of a medical nature, complete in colour and show cancer of the colon, observed in Figure 4.12a. Therefore, the core research goal is improving parameters of performance for image compression in less reduced while maintaining similar quality-levels as the originator.

The LRCCT-HVS method incorporates the following activity:

Step 1: Reversible Colour Technique:

- RGB-based colour image in inputted, then converted to a Y-CuCv colour-space through RCT optimization.

As an example for compression that is lossless, the YC_bC_r transformation being used is defined:

$$\begin{pmatrix} Y \\ C_b \\ C_r \end{pmatrix} = \begin{pmatrix} 0.299 & 0.587 & 0.114 \\ -0.16875 & -0.33126 & 0.5 \\ 0.5 & -0.41869 & -0.08131 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} \tag{4.5}$$

Which has an inverse given by:

$$\begin{pmatrix} R \\ G \\ B \end{pmatrix} = \begin{pmatrix} 1 & 1.402 & 0 \\ 1 & 0 & 1.772 \\ 1 & -0.714 & -0.344 \end{pmatrix} \begin{pmatrix} Y \\ C_b \\ C_r \end{pmatrix} \tag{4.6}$$

The JPEG2000 Reversible Colour Transform (RCT) is a YC_uC_v like colour space that does not introduce quantization errors which is also introduces noise and also is the difference between an input value and its quantized value (see step 3 section 4.2.1), as it can be reversed.

For JPEG2000, a reversible colour transform (RCT) and then compresses the image is presented in Equation 4.7 follows:

$$Y = \frac{(R + 2G + B)}{4} \tag{4.7}$$

$$C_u = R–G \leftrightarrow R = C_u + G$$

$$C_v = B - G \leftrightarrow B = C_v + G$$

The de-compressor then de-compresses the image, taking YC_uC_v pixels and restoring original RGB imaging with Equation 4.8:

$$G = \frac{Y - (C_u + C_v)}{4} \tag{4.8}$$

Both Equation 4.7 and Equation 4.8 form a simple-based transform. The transform is refereed to "the reversible" transform as it is invertible with arithmetic of integers. However, the satisfaction of performing de-correlation is not offered. By decorrelation, it is a general term referring to the process of reducing autocorrelation in a signal while maintaining other signal elements (Pasteau et al. (2009)).

A pixel in the JPEG2000 YC_uC_v format requires bits of 26 in length to present losslessness. The Green, Blue and Red layers of a digital image are usually correlated in a high manner. So the compression of Green, Blue and Red layers in an independent manner results in storing a lot of the data three times. Although decorrelation of 24-bit/pixel RGB digital image in YC_uC_v demands greater bits to represent every pixel, so decorrelation assist the other stages in the pipeline of compression. The independent compression of Y, C_u, and C_v planes leads to a smaller file that is compressed instead of compressing RGB layers of an equivalent file. For lossless reversible colour transformation the 5/3 wavelet filter is generally employed (Adams (2002)). Its implementation complexity is low, moreover the execution time of 5/3 wavelet filter is more rapid than say the 9/7 Daubechies filter (Khemiri et al. (2016)).

Step 2: 5D Discrete Wavelet Transform (5D-DWT) based on JPEG2000:

- Image source is 5D-DWT encoded and for every component in a 8 by 8 block segment, which undergoes wavelet transformation (step 2 section 4.1.2).

Step 3: Quantization Step:

- After that, only significant relevant lossless data is employed and the other insignificant data which is repeated data could be rejected by the quantizer step. Huffman entropy-based coder is lossless (section 3.2.2 No.2), which follows the quantization process. In the case that the quantizer is loss-less, the image that is reconstructed is equivalent to the original image.
- Lossless compression based technique employs a matrix of quantization, whereby the element comprise of ones. Thresholding (section 4.1.2 step 5) is chosen on HVS basis, and parameters of performance are computed with a check known as "Post Compression Rate Distortion-Optimization" (PCRD-OP) check (Liu et al. (2006)).

Step 4: Inverse RCT and DWT:

- Application of the RCT that is inverse, along with the RDWT that is inverse that enables pixel data to be loss-lessly recoverable in the image encoder process.

Step 5: Achieve the Optimum Performance:

- As per section 4.1.2 step 8, in the process of training - the properties of compression are verified and only if performance is at its optimum in the approach as selected, the optimum solution is the proposed last step.
- Else, repeat the step of training.
- At the end, the proposed solution for images is provided.

The core loss-less methodology for compression of images are summarized in the Algorithm 4.2. The steps above are shown at Figure 4.10.

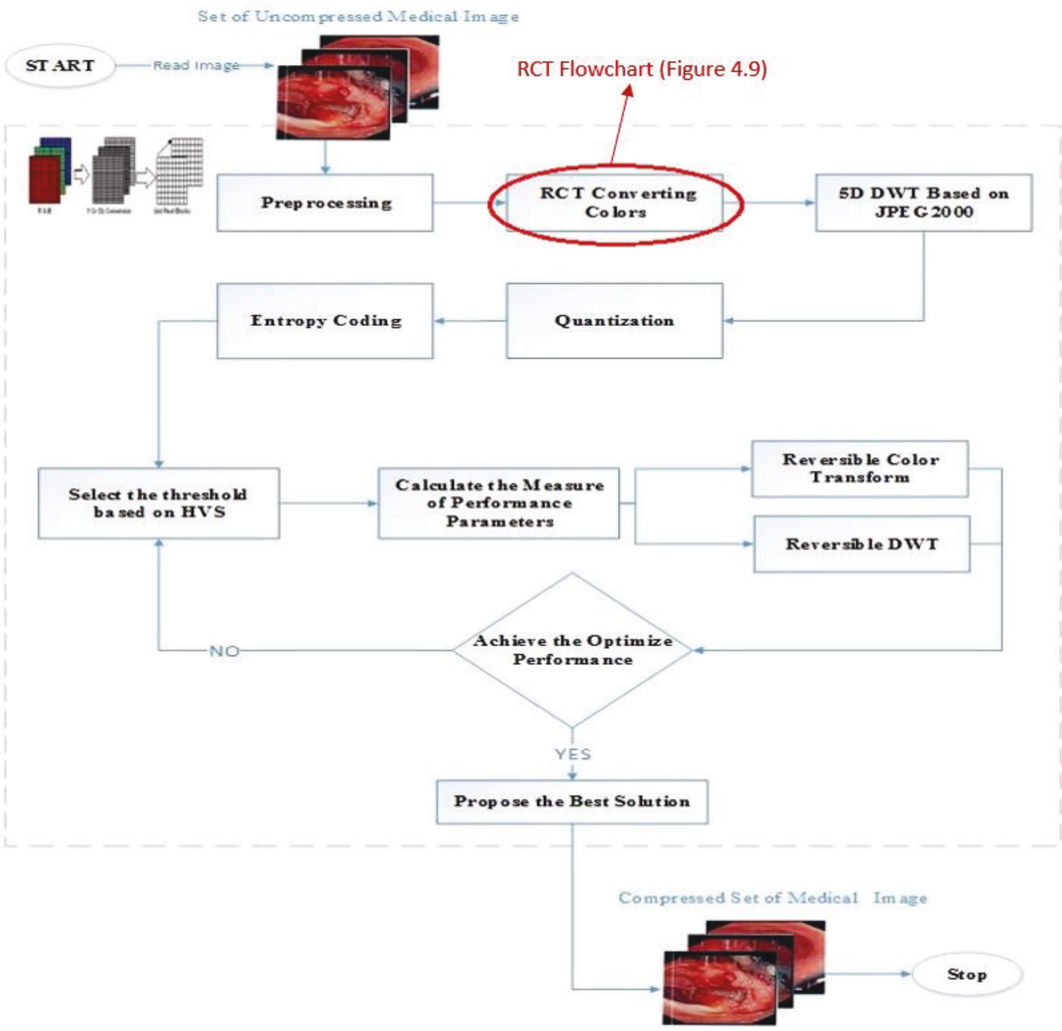


Figure 4.10: LRCCT-HVS proposed method flowchart

Algorithm 4.2 Procedure for LRCCT-HVS method using RCT with HVS

1: Start
2: Input Image A, $[r, c]$= size (A)
3: Output: A_c' (Compressed A)
4: Convert A $(RGB) \rightarrow A$' $(YC_uC_v$) using RCT
Apply Wavelet Transform: $y[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k]$, W= 5 db (Wavelet) to the images
6: Divide the image into blocks
    Do quantization
7: While $k = 1 : 3$ Do Select Methods Using HVS, K(Number of elements in array)
        If $K == 1$ Select NVF then
            Else If $K == 2$ Select JND then
             Else If $K == 3$ Select CSF
        End If
  End While
8: Calculate $|P|$ which is performance parameters
        If $|P| < N$ (N = Best Result) then
            Do repeat encoding step then
                Else If $|P| \geq N$
        End If
9: Display A_c' (output)

The entropy coding of images of a medical nature is different from that of other image sources, because ensuring the integrity of specific information such as diagnostics is preserved while attempting to minimize the requirements of persistence and transmission (Wu et al. (2006)).

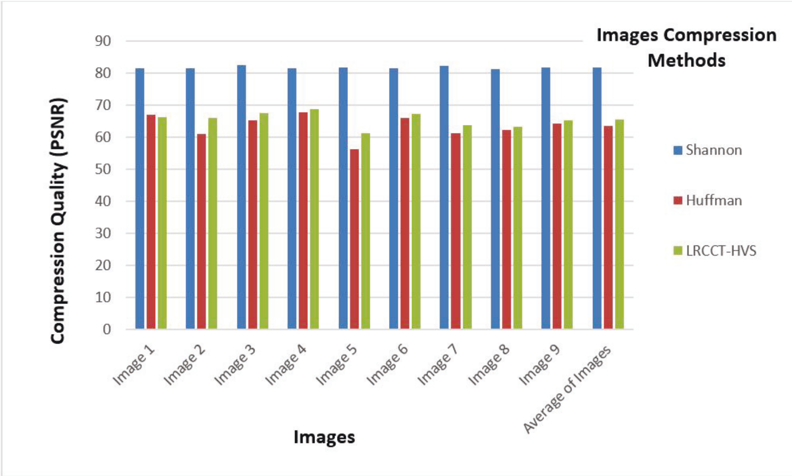
Lossless compression method applies when information loss cannot be tolerated because it is critical. Images that are medical in nature typically require high memory resources including MRI or Magnetic Resonance Imaging, and CT or Computed Tomography. Because of persistence and transmission limitations, the primary concern is about the ability to compress the visual information that is of a a low bitrate, simply because the quantity of medical-based images would exhaust storage capability without effective compression techniques.

When entropy coding of medical images it is imperative that the diagnostic data is is maintained while also reducing storage, along with networking resources. As a result, the optimum approach is through reversible-based compression (Wu et al. (2006)). Medical imaging is been used for the diagnosis of diseases and surgical planning, and needs long-term storage for profiling patient's data. In the field of online diagnosis or real-time applications such as telemedicine, demands for hardware to handle lossless compression that can accelerate the computation process is required. The medical image, which is a subjectively chosen target for testing this method. And to illustrate this criticality, a general medical image was chosen.

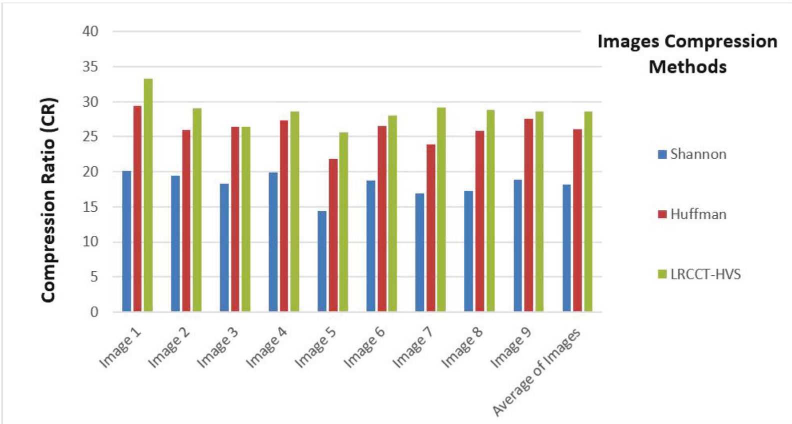
4.3.3 Experimental Results

In the work presented, the technique of compression that is lossless is effectively optimized to accomplish the goal of the research. Proposed methodology was computed utilizing MATLAB code as per Algorithm 4.2 and depicted in Figure 4.11. Additionally this section utilizes 9 images for Colon Cancer, as shown at Figure 4.12. These shows that the 5D-based wavelet for the technique that is lossless accomplishes results that are positive: including the ratio of compression (30% and above) and high quality with PSNR (50% and above) and SSIM (near to 1). The approach assesses the quality of compression, ratio of compression and image that is compressed to be equivalent to the originating source presented in Table 4.3 and Table 4.5.

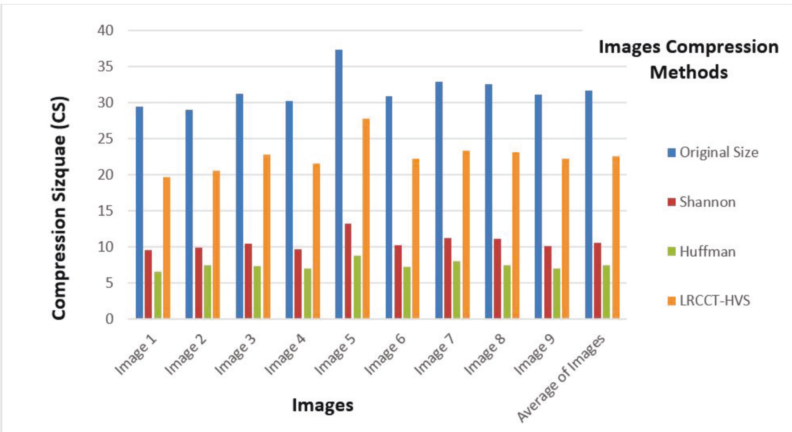
Clearly from Figure 4.11a, Figure 4.11b and Figure 4.11c, a connection exists with compression ratio, quality and size of compression. As shown at Figure 4.11a the result of Matlab code the PSNR for a various lossless compression techniques, the proposed method present quality (above 60%) as show at Table 4.4. The compression ratio for proposed method shown at Table 4.5 and Figure 4.11b which present a higher compression ratio (above 30%) in lossless domain because if go higher that mean a lot of data will lose, in this case the image that is compressed should be similar to the originating source. Referring to the size of the image that is compressed and the original after application of the specified method can be observed in Table 4.6. From the comparison in this paper (Hakami & Chaczko (2017)) will found the value of compression ratio between 33.34% into 28.63% as shown at Table 4.5. Figure 4.11c illustrate the compressed image for proposed method similar to the original image. There is always balance between compression quality, compression ratio and compression size. From Figure 4.11a a Shannon get a higher compression quality but compression ratio is low. However, the compressed image from proposed method achieve the balance between research aim as present it (section 1.5).



(a) Compression quality for stated methodologies

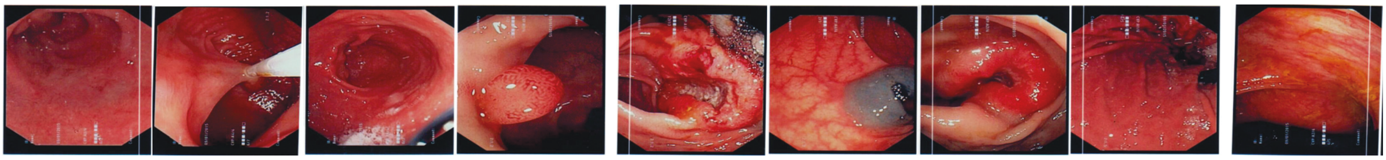


(b) Compression ratio for stated methodologies

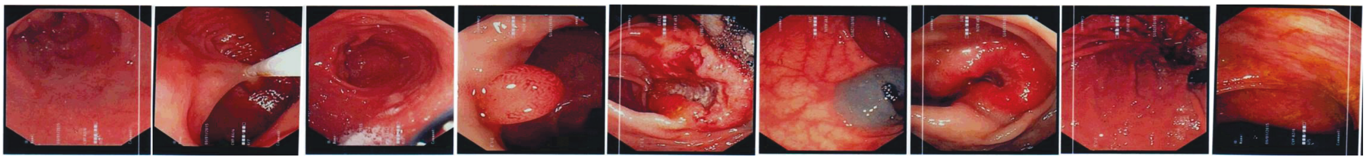


(c) Compression size for stated methodologies

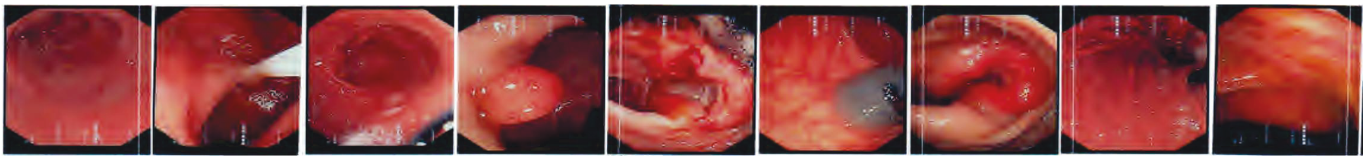
Figure 4.11: The performance evaluation parameters for Lossless methodologies (Matlab Code)



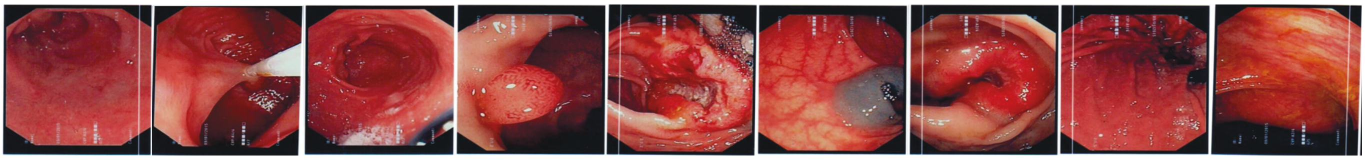
(a) Cancer of the colon (original source images)



(b) Cancer of the colon (Shannon-based coding)



(c) Cancer of the colon (Huffman-based coding)



(d) Cancer of the colon (LRCCT-HVS proposed method)

Figure 4.12: Proposed Method Result Using RCT With HVS

Images	PSNR	MSE	SSIM
Image1	66.41	0.014	0.9996
Image2	66.18	0.015	0.9997
Image3	67.55	0.011	0.9998
Image4	68.89	0.008	0.9998
Image5	61.26	0.048	0.9995
Image6	67.38	0.011	0.9998
Image7	63.88	0.026	0.9996
Image8	63.30	0.022	0.9996
Image9	65.33	0.019	0.9997
Average of Images	65.575	0.0193	0.9999

Table 4.3: Proposed methodology evaluation of quality

Compression Quality Evaluation for Various Lossless Methods			
Images	Shannon	Huffman	LRCCT-HVS
Image1	81.6	67.17	66.41
Image2	81.56	61.01	66.18
Image3	82.62	65.41	67.55
Image4	81.64	67.84	68.89
Image5	81.71	56.32	61.26
Image6	81.45	66.01	67.38
Image7	82.24	61.22	63.88
Image8	81.36	62.28	63.30
Image9	81.91	64.30	65.33
Average of Images	81.78	63.50	63.57

Table 4.4: Comparison of compression quality for various lossless methods

Compression Ratio (%) Evaluation for Various Lossless Methods			
Images	Shannon	Huffman	LRCCT-HVS
Image1	20.12	29.41	33.34
Image2	19.49	26.02	29.08
Image3	18.29	26.39	26.48
Image4	19.94	27.37	28.58
Image5	14.45	21.87	25.66
Image6	18.82	26.59	28.06
Image7	16.99	23.96	29.18
Image8	17.24	25.8	28.88
Image9	18.91	27.61	28.58
Average of Images	18.25	26.11	28.63

Table 4.5: Comparison of compression ratio for various lossless methods

Compression Size (KB) Evaluation for Various Lossless Methods				
Images	Original Size	Shannon	Huffman	LRCCT-HVS
Image 1	29.46	9.53	6.52	19.6
Image 2	28.92	9.84	7.37	20.5
Image 3	31.19	10.4	7.27	22.8
Image 4	30.20	9.62	7.01	21.5
Image 5	37.28	13.2	8.77	27.7
Image 6	30.91	10.2	7.21	22.2
Image 7	32.90	11.2	8.01	23.3
Image8	32.50	11.1	7.43	23.1
Image 9	31.08	10.1	6.95	22.2
Average of Images	31.60	10.57	7.39	22.54

Table 4.6: Comparison of compression size for various lossless methods

4.4 Efficient Image Enhancement for Compression Techniques using Human Visual System

4.4.1 The Problem

Utilizing from chunk 1 (section 4.1: Lossy Compression) and the conclusion shown at the end of the chapter, the Peak Signal to Noise Ratio (PSNR), Structural Similarity Index Modulation (SSIM) and Mean Square Error (MSE) which are focused in chunk 2 (section 4.2: Lossless Compression) is describe as the performance measurements of the enhancement compression techniques.

This research start with lossy compression technique to present data in less redundant for storing, transmitting and retrieving data in less time. Follow by lossless compression technique dealing with less redundant in less time while maintaining same quality similar to original. Both compression techniques will end with enhancement techniques to achieve best result.

Image compressing and enhancement approaches are common techniques in the realm of imaging. This chapter compares the performance quality of different compression includes: (EZW, JPEG2000, Huffman, Shannon, IECT lossy and IECT lossless) and enhancement techniques includes: (DSIHE, BHEMHB, MVSIHE and ESIHE) basing on various performance-based metrics of data compression.

The main idea is to factor various digital imaging and undertake techniques of compression. The imaging is then restored through the process of enhancement. Afterwards, performance measurements of the compression and enhancement techniques is calculated by using Histogram Evaluation (HE) to increase the compressed image contrast with removing the noise. After the enhancement compressed image start to calculate the quality measurement with performance parametric criteria like Mean Square Error (MSE), Structural Similarity Index Modulation (SSIM) and Peak Signal to Noise Ratio (PSNR).

As a result of increased communication demands over time; the necessity for image compression has become paramount. Image compression algorithms using wavelets are developed, offering considerable improvements in the quality of images ratios of compression that are high. To accomplish reduced errors/compression ratio and raise quality of perception, existent image algorithms of compression require modification. This was accomplished with MATLAB and results demonstrate the ratio of compression ratio rises without impacting on the PSNR or Peak Signal to Noise Ratio (Kranthi, B., Kamaraju, M., Krishna, B.A. and Rajasekhar (2014)).

Greater than 70% of the data obtained by an individual person is done through vision essentially (Kaur & Kaur (2014)). In comparison with other information types, imaging is precise and intuitive, although it factors a great information amount. Thus, imaging form a large portion of modern transmission, storage and digital information processing. Due to the great amount of information contained in digital imaging, speeds of transmission are impacted, and capacity of storage are affected. The stated factors have thus limited the image communication development; but invigorated the research into technologies of compressing images (Liu et al. (2018)).

The driver of compression of images is to minimize the data amount as greatly as possible, with the premise being that the re-constructed image is of quality while satisfying application-based needs. Recently, research into compression of images are done, with much technologies of image standards and coding developed over time (Bairagi et al. (2013)). This involves technology into image compression using wavelet transform, fractal theories and human visual characteristics. Although, the sensitivity characteristics of contrast for the human visual system (HVS) are not taken advantage in the area of image compression in colour. As an example in 2010, Sathidevi and Sreelekha presented an quantization scheme that is adaptive being based upon human visual characteristics for colour image compression. Although high compression ratios are achieved, the complexity of the algorithm results in a greater time to run (Yao & Liu (2017)).

To result in greater compression ratios of images and optimize perception of an image that is decompressed, an image compression scheme based on colour using sensitivity characteristics of contrast utilize the human visual system (HVS). Results show that image compression schemes in colour is effective and feasible to accomplish greater ratios of compression ratios while preserving image quality and encoding, which thus meets the daily need for transmission and storage of colour imaging (Yao & Liu (2017)).

4.4.2 Proposed Method (IECT)

The result of the previous work (sections 4.1 and 4.2) has lead to this particular Image Enhancement Compression Technique (IECT). The goal of this proposed method (IECT) is to enhance the images after compression by modifying the dynamic range, contrast or both factors. Therefore, increasing the image contrast, reducing the overall dynamic range and removing the noise can significantly enhance the quality of an image. Basically, IECT uses Histogram Equalization (HE) based on HVS applied to many types of images, inclusive of medical and other images. Histogram equalization is an operation applicable to produce new imaging based on histogram modification or specification, as considered a technique globally. The process is straightforward, and for brightness j in the source, new pixel level (k) is computed as Equation 4.9 bellow:

$$\sum_{i=0}^{j} \frac{N_i}{T} \tag{4.9}$$

Where the sum counts the pixel number with brightness less than or equal to j, and T is total pixel number. The primary reason of equalization of the histogram is discovering greylevel transformation function T to transform imaging f as such histogram of $T(f)$ is equalized.

Image Enhancement Compression Technique (IECT) is one of the critical techniques to optimizing the perception or interpretation of data in imaging for humans, and offering optimum input for other automatic imaging processors. After compression, it is required to improve the contrast and remove noisiness to raise quality of the image. During enhancements after a compressed image, the modification of image attributes is the main objective. To adjust attributes of an image leads it to be suitable for a specific task and given observer. The attribute choices and the way of modification are specific to the task.

In addition, factors specific to an observer, such as the human visual system and the experiences of the given observer, will lead to a deal of subjective qualities into the selection of enhancement methods for images (Aggarwal & Himanshu (2010)). To increase image quality it is required to enhance its brightness, contrast and eliminate any noisiness using histogram evaluation as depicted in Figure 4.13. Figure 4.13 shows a flowchart for image enhancement techniques to increase compressed image resolution.

An important stage in the detection of medical imaging and analysis is the techniques of imaging enhancement that optimizes the clarifies digital images for medical personnel, reducing noisiness and blurring, raising contrasts and discovering distinct details are demonstrable examples of enhancement operations (Thakral, M.D. and Sandhu (2014)).

This method has using MATLAB work explained in the steps as presented in Figure 4.14. The IECT method incorporates the following activity:

Step 1: Pre-processing Input Images:

- In this step selecting the image format, in order to analyze image size, colour and image noise.
- A histogram functions to plot each grey-level frequency between 0 (black) and 255 (white). The first prepossessing step should be the Histogram process. Histogram equalization is the process applied to generate new images emergent from the histogram specification or modification. The process, which is applied globally, is simple whereby a new pixel level value (r_k) is calculated for each brightness level (n_k) in the original image. This Equation 4.10 is expressed as follows:

  $$h(r_k) = n_k/N \tag{4.10}$$

Where

r_k and n_k are intensity level and number of pixels in image with intensity respectively.

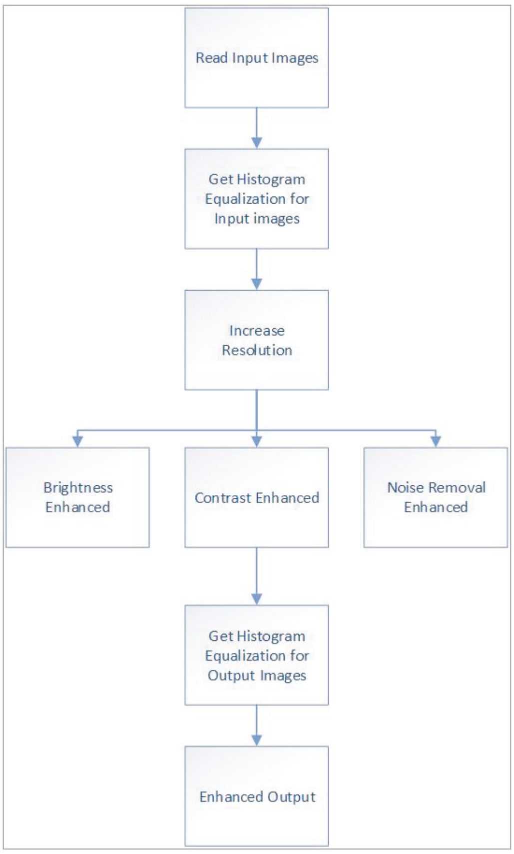


Figure 4.13: Image Enhancement Techniques (IET) flowchart

Step 2: Select Compression Type:

- This step has two ways, first select Lossy Compression (LCT-HVS) and start to calculate performance parameters. Second select Lossless Compression (LRCCT-HVS) and also start to calculate performance parameters.
- Then compare the assess similarity for measure the quality.
- Generates the histograms and bars for compressed images.
- Evaluate the result for both compression techniques.

Step 3: Enhancement Process:

This step is undertaken to improve the contrast in the compressed image by preserving the brightness. For image compression, the IECT utilizes the spatial domain focusing on contrast and brightness. A spatial domain is the aggregate of pixels within an image. The spatial domain image process is performed directly over the pixels and is represented by the Equation 4.11:

$$g(x, y) = \tau[f(x, y)] \tag{4.11}$$

Where

$f(x, y)$ and $g(x, y)$ represent the input image and the processed image, respectively via mathematical mapping τ defined over (x, y). This mapping/operator is applied to an arbitrary coordinate point (x, y) to achieve an identical processed point coordinate (x, y). This mathematical mapping τ is referred to as intensity mapping or grey-level transformation (Das (2015)).When r and s represent the arbitrary point's intensity prior to and following the transformation, Equation 4.12 is rewritten as follows:

$$s = \tau[r] \tag{4.12}$$

In IECT method includes other methods for enhancement such as:

- Dualistic Sub-image Histogram Equalization (DSIHE), employ a median value to the separation intensity so that the histogram can be divided into two sub-histograms (Yao et al. (1999)).
- Bi-hisogram Equalization Modified Histogram Bins (BHEMHB), allow for the segmentation of the input histogram according to the image's median brightness. It also modifies the histogram bins prior to the application of the HE. Histogram segmentation supports preservation of the average brightness; whereas, the histogram bin modifications constrain the rate of enhancement and therefore minimizes the dominating impacts of the high-frequency histogram bins (Tang & Mat Isa (2017)).
- Mean and Variance based Sub-image Histogram Equalization (MVSIHE), refers to the method for decomposing an original image down to two sub-images. This is achieved by determining the average grey level of the image and then applying the HE technique to each sub image individually. This allows for two histograms to be obtained: one that holds the high-intensity pixels and one that holds the low-intensity pixels. The selection of the separating point is then made based on as the average grey level of the input image (Zhuang & Guan (2017)).
- Exposure threshold based Sub-Image Histogram Equalization (ESIHE), refers to the method to enhance the contrast in a low-exposure grey scale image. The method involves division of the original image into two sub-images; namely, an under exposed and an over exposed image) according to the exposure threshold value presented as follows in Equation 4.13:

$$exposure = \frac{1}{L} \frac{\sum_{k=1}^{L} h(k)k}{\sum_{k=1}^{L} h(k)} \tag{4.13}$$

Where

L= total no of grey level and $h(k)$ = image histogram (Kapoor, K. and Arora (2015)).

Step 4: Evaluate Achieve Optimize Output:

- In this step check the properties of enhanced the compression image if optimized performance is accomplished, the final step is proposed as best outcome.
- Else the step of training is repeated (go back to step 3).
- Finally, the best solution for the enhanced compressed image is proposed.

Furthermore, the Algorithm 4.3 explains the functional steps of the IECT for filtering the compressed image.

Algorithm 4.3 Procedure of proposed method (IECT)

1: Start
2: Input Images A , $[r, c]$= size (A)
3: Output: A'_c (Enhanced Compressed Images A)
4: Select Compression Type: L_1= Lossy Compression Technique (LCT-HVS), L_2 = Lossless Compression Technique (LRCCT-HVS)
5: Define $|P|$ = Performance Parameters
 If $L_1 \leq 1$
Then Calculate $|P|$
  End If
   Else If $L_2 \geq 1$
Then Calculate $|P|$
    End If
6: Display A'_c for $L_1$and L_2
7: Define Enhanced Techniques (ET)
$While A'_c < I$ (Different)
  execute ET for A'_c with HE which is Histogram Equalization
  execute ET for A'_c with $BBHE$ which is Brightness Bit Histogram Equalization
  execute ET for A'_c by Removing Noise
 End $While$
  else If $A'_c == I$ (Similar) No need for ET
   End $eLse$
    End If
6. Display output(A'_c)

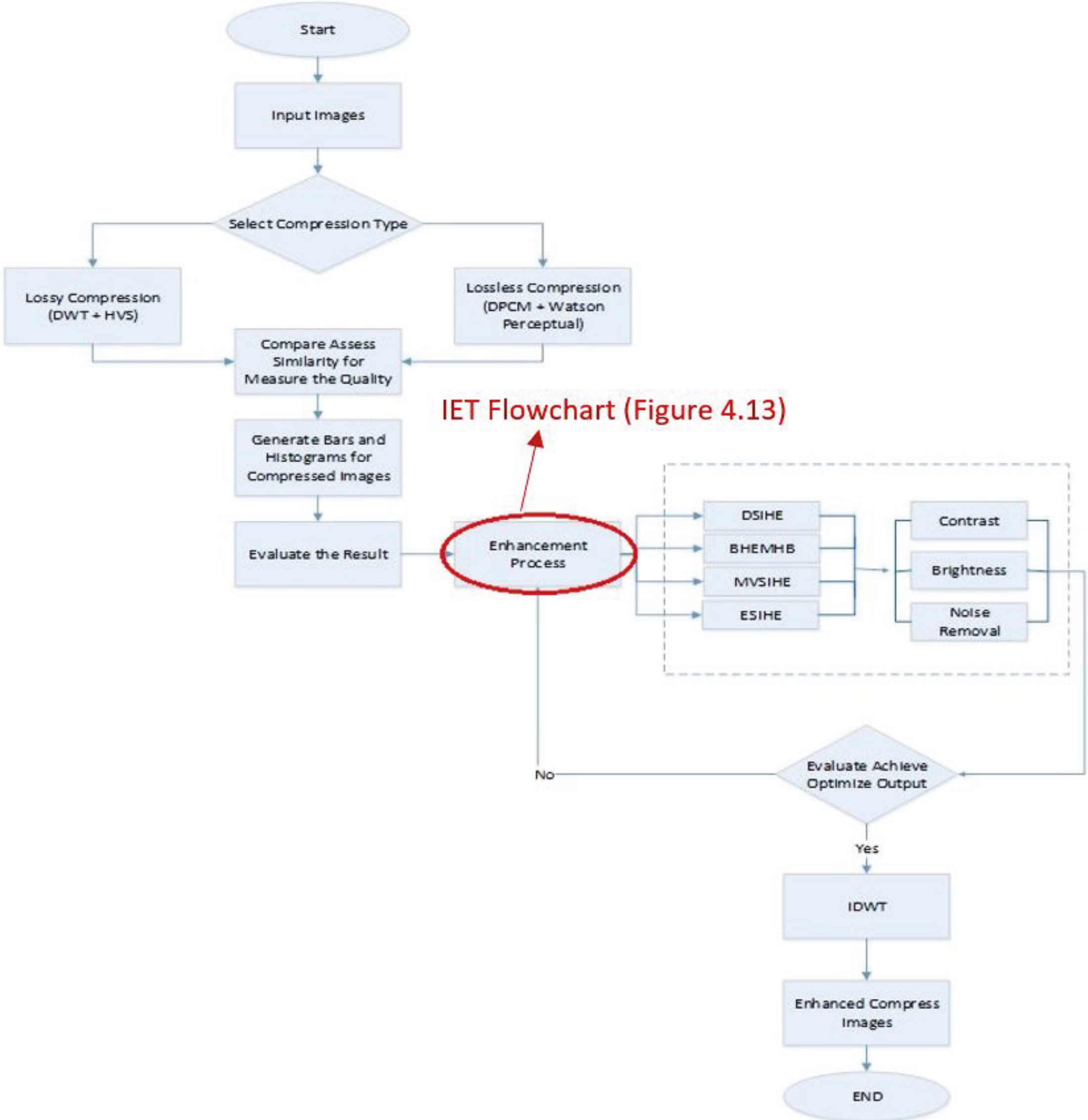


Figure 4.14: IECT proposed method flowchart

4.4.3 Experimental Results

This chapter focuses on enhanced compressed images for which the quality measurement is critical. Experimentation includes a collection of selected performance metrics and plots the graphs for the values obtained. The utilization of 10 images from the Uncompressed Colour Image Dataset (UCID) as per (Stich, M. and Schaefer (2004)) has been used by this research.

Figure 4.15 present the result of brightness enhancement methods before and after applying the IECT lossy compression techniques. Figure 4.16 shows the comparison for contrast enhancement methods before and after IECT lossy compression techniques. Whereas, Figure 4.17 present the comparison for the noise removal enhancement methods before and after IECT lossy compression techniques.

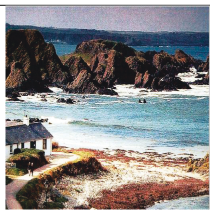
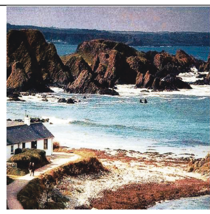
Enhancement Methods	Original Image	Brightness Enhancement Before Compression	Brightness Enhancement After Compression
DSIHE			
BHEMHB			
MVSIHE			

Figure 4.15: Brightness enhancement result

Figure 4.19 present a histogram equalization for IECT lossy and shows the histogram of differences between the original image and the IECT lossy compressed image. Figure 4.18 also present the histogram equalization for the IECT lossless compressed image and also shows the differences between original image and IECT lossy compressed image. From Figure 4.19 and Figure 4.18 a different was found between those images utilizing the histogram equalization for IECT lossy compressed images. These differences were not the same as for the IECT lossless.

Performance of the enhanced IECT lossy and lossless compressed images includes four (4) parameters: Peak Signal to Noise Ratio (PSNR), Compression Ratio (CR), Compression Size (CS) and Compression Time (CT).

Figure 4.20 represents the evaluation of 3 different lossy compression methods which includes: EZW, JPEG2000 and IECT lossy. After analyzing the results graphed in

Figure 4.16: Contrast enhancement result

Figure 4.20 the IECT lossy compressed method provides a good compression ratio (above 60%). Moreover, the results of other parameters show a satisfactory result for compression quality and compression time.

Figure 4.21 also represents the evaluation of another 3 different lossless compression methods which includes: Huffman, Shannon and IECT lossless. IECT lossless offers the highest compression (average 40% KB of information) of an original image as shown at Figure 4.21. Equally, image quality is also higher - Shannon compared is higher than the other methods.

Figure 4.22 and Figure 4.23 present the results of the 6 compression methods.

Quality of the enhanced compressed image is the highest for IECT lossy compression than for other methods as shown at Table 4.7. The first column in Table 4.7 indicates the original images. Second and third columns show the number of image quality for lossy compression methods (EZW, JPEG2000). Finally, last column shows the numbers of image quality for IECT lossy compression. Shannon compression has a higher quality than other methods as shown at Table 4.8.

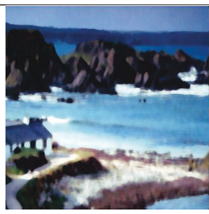
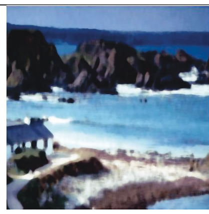
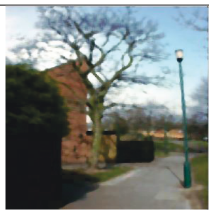
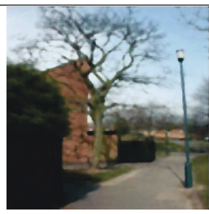
Enhancement Methods	Original Image	Noise Removal Enhancement Before Compression	Noise Removal Enhancement After Compression
DSIHE			
BHEMHB			
MVSIHE			

Figure 4.17: Noise removal enhancement result

Images	EZW	JPEG2000	IECT Lossy
1	60.43	39.39	73.47372
2	66.42	55.45	67.25925
3	71.97	67.24	58.13442
4	64.63	51.56	69.88566
5	64.90	56.57	68.9153
6	65.82	55.33	69.06339
7	74.39	70.69	60.50856
8	68.71	60.85	66.83978
9	70.44	64.44	58.85477
Average of Images	63.02	55.13	65.66931

Table 4.7: Quality evaluation result for IECT lossy compression methods

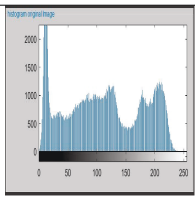
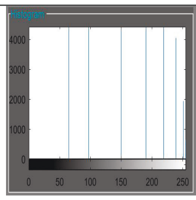
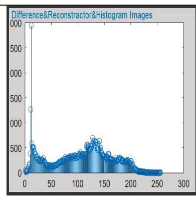
Original Images	Histogram Equalization for Original Image	Histogram Equalization for IECT Lossy Compression Techniques	Different between two Images
			

Figure 4.18: Histogram equalization for lossless compression technique

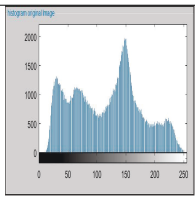
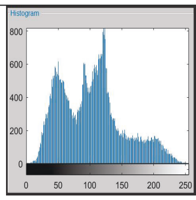
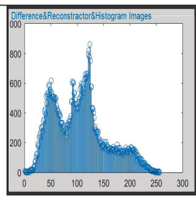
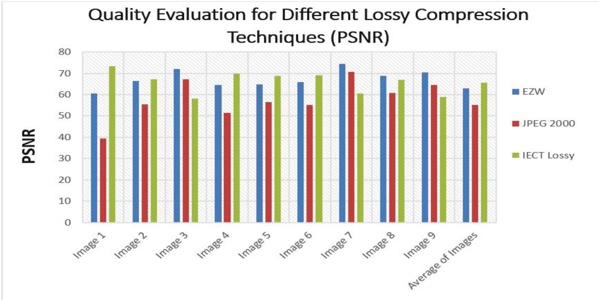
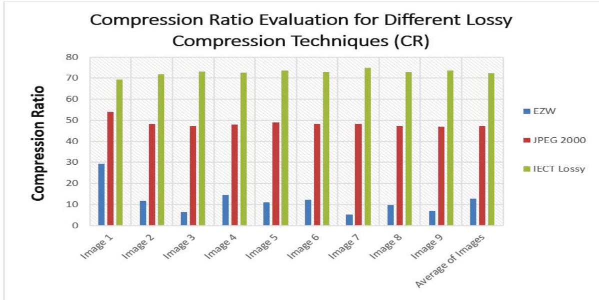
Original Images	Histogram Equalization for Original Image	Histogram Equalization for IECT Lossless Compression Techniques	Different between two Images
			

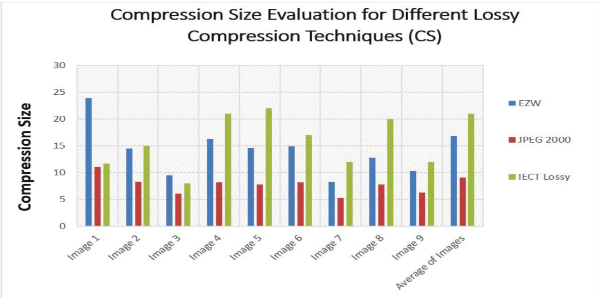
Figure 4.19: Histogram equalization for lossy compression technique



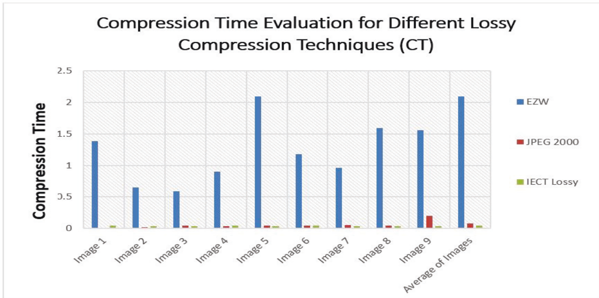
Compression Quality



Compression Ratio

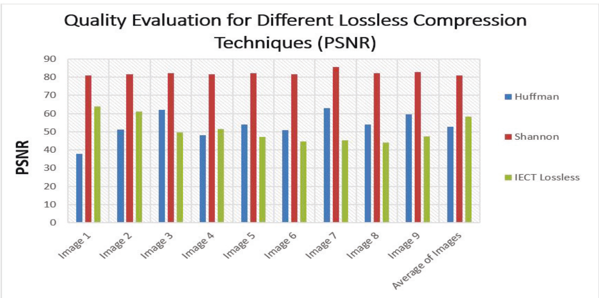


Compression Size

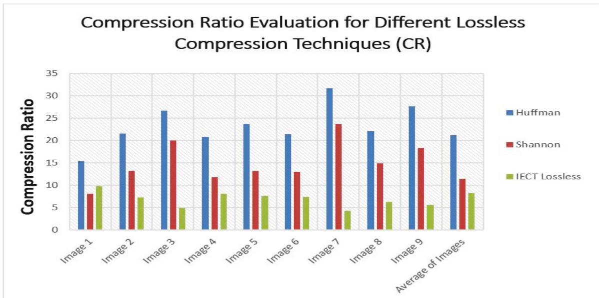


Compression Time

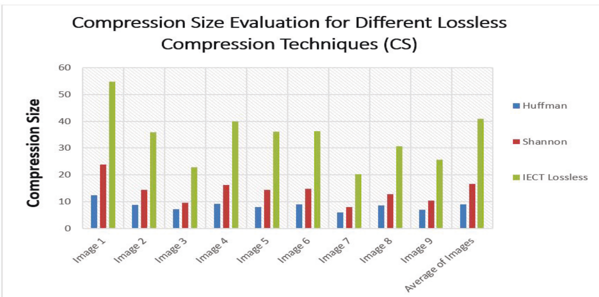
Figure 4.20: Evaluation of performance parameters for listed Lossy compression methodologies



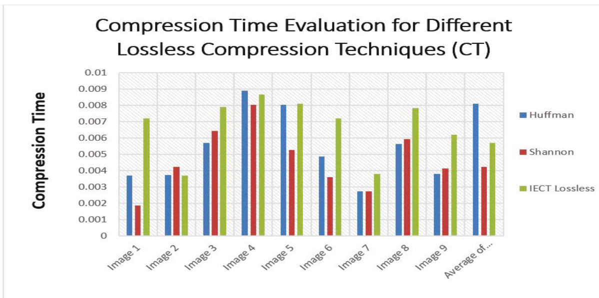
Compression Quality



Compression Ratio



Compression Size



Compression Time

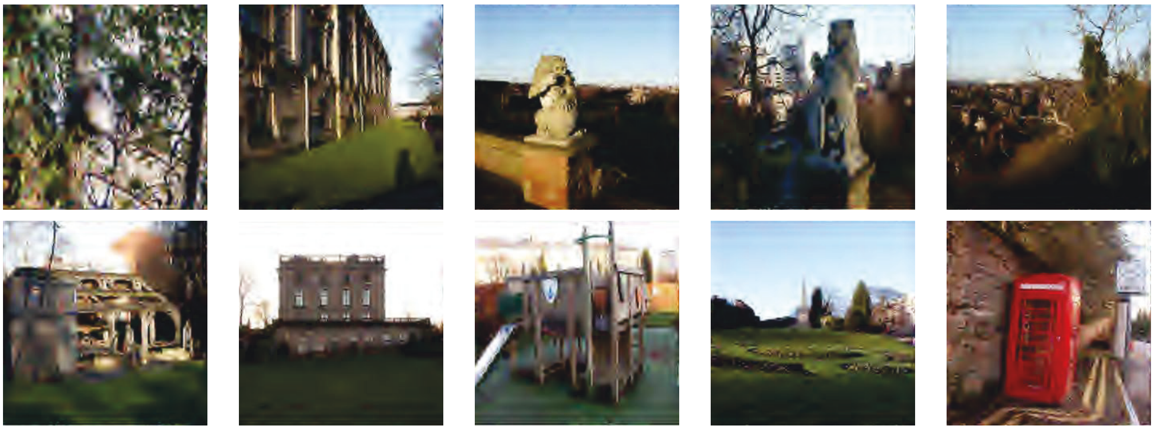
Figure 4.21: Evaluation of performance parameters for listed Lossless compression methodologies

(a) EZW compressed images

(b) JPEG2000 compressed image

(c) IECT lossy

Figure 4.22: Lossy compression methods evaluation



(a) Huffman compressed images

(b) Shannon compressed images

(c) IECT lossless

Figure 4.23: Lossless compression methods evaluation

Images	Huffman	Shannon	IECT Lossless
1	37.82	81.07	63.77149
2	51.10	81.47	61.08379
3	62.05	82.16	49.50392
4	48.19	81.67	51.4960
5	53.94	82.02	47.29463
6	50.79	81.44	44.72324
7	63.02	85.71	45.41663
8	53.90	82.18	44.06711
9	59.56	82.65	47.36454
Average of Images	52.81	80.89	58.32999

Table 4.8: Quality evaluation result for IECT lossless compression methods

Table 4.9 indicates compression ratio results for original images - enhanced images - compressed images for 6 compression methods. These ratios are found using formula (see section 2.6.2). These results very widely in value for each of the 6 compression methods. IECT lossy has higher compression ratio (above 60%) more than the other lossy methods. To keep more information similar to its original image the compression ratio in this case has to be no more than 20% in IECT lossless compression. IECT lossless is the best at a maximum of 10% as shown at Table 4.10.

Compression Ratio (%)			
Images	EZW	JPEG2000	IECT Lossy
1	29.39	54.02	69.4455
2	11.82	48.08	71.8927
3	6.54	47.18	73.0552
4	14.38	47.94	72.6296
5	10.86	49.01	73.5093
6	12.28	48.29	72.8675
7	5.16	48.15	74.9022
8	9.5	47.28	72.8388
9	7	47.04	73.5682
Average of Images	12.82	47.25	72.2487

Table 4.9: Compression ratio evaluation result for IECT lossy compression methods

Compression Ratio (%)			
Images	Huffman	Shannon	IECT Lossless
1	15.34	8.03	9.739898
2	21.46	13.23	7.211487
3	26.61	20.01	4.885868
4	20.86	11.75	8.071019
5	23.68	13.17	7.613928
6	21.41	12.92	7.348289
7	31.68	23.71	4.307077
8	22.1	14.86	6.305662
9	27.54	18.35	5.606298
Average of Images	21.15	11.43	8.195274

Table 4.10: Compression ratio evaluation result for IECT lossless compression methods

Table 4.11 present the compression size for all 6 compression methods. Shown the primary aim for data compression is to reduce data size. As all these 6 compression methods achieved this aim with different values. During the compression process no more one second for every image is needed, so these 6 methods compressed the data in less time as shown at Table 4.13 and Table 4.14.

Compression Size (KB)			
Images	EZW	JPEG2000	IECT Lossy
1	23.91	11.10	11.7
2	14.45	8.33	15
3	9.51	6.11	8
4	16.34	8.23	21
5	14.61	7.80	22
6	14.90	8.24	17
7	8.33	5.25	12
8	12.82	7.78	20
9	10.30	6.26	12
Average of Images	16.77	9.07	15.3

Table 4.11: Compression size evaluation result for IECT lossy compression methods

Compression Size (KB)			
Images	Huffman	Shannon	IECT Lossless
1	12.5	23.8	54.8
2	8.94	14.5	35.8
3	7.21	9.59	22.8
4	9.20	16.3	39.9
5	8.10	14.5	36.1
6	8.96	14.8	36.2
7	6.05	8.09	20.2
8	8.68	12.9	30.7
9	6.97	10.4	25.7
Average of Images	9.07	16.7	40.9

Table 4.12: Compression size evaluation result for IECT lossless compression methods

Compression Time (Seconds)			
Images	EZW	JPEG2000	IECT Lossy
1	1.3824	0.006681	0.03921
2	0.6517	0.017505	0.03825
3	0.5886	0.044348	0.03424
4	0.9020	0.03353	0.04632
5	2.0938	0.041983	0.03690
6	1.1790	0.043162	0.04148
7	0.9643	0.053844	0.03700
8	1.5907	0.043631	0.03522
9	1.5610	0.197858	0.03484
Average of Images	2.0974	0.07631	0.04451

Table 4.13: Compression time evaluation result for IECT lossy compression methods

Compression Time (Seconds)			
Images	Huffman	Shannon	IECT Lossless
1	0.000037	0.000018	0.00721501
2	0.000037	0.000042	0.3046867
3	0.000057	0.000064	0.0079080
4	0.000088	0.000080	0.008661
5	0.000804	0.000527	0.008980
6	0.000048	0.000036	0.0074118
7	0.000027	0.000027	0.0038147
8	0.000056	0.000059	0.0078398
9	0.000038	0.000041	0.0062183
Average of Images	0.000081	0.000042	0.005705

Table 4.14: Compression time evaluation result for IECT lossless compression methods

The experimental result shows consecutively that both IECT lossy and lossless methods are effective and efficient in enhancing the compressed image. The relationship of the balance between performance parameters as shown at chapter 1, is also achieved.

4.5 Summary

The main purpose of this chapter is to analyze the performance parameters for enhancement compression techniques. Image enhancement algorithms offer a wide variety of approaches for modifying images to achieve acceptable image quality. The choice of such techniques is a function of the specific task, image content, observer characteristics, and viewing conditions. Experimental methods of data comparison techniques using wavelet transform-based HVS presented in this chapter. From the results and analysis of these data compression methods have calculated PSNR, CR, CS and CT to evaluate the image quality based on the HVS.

The Chapter presented a new method of data compression, is an essential approach to reduce redundancy, size of data and the time required storing and handling data with high rates of quality. In particular circumstances, the initial multimedia is needed with no information loss such as IECT lossless. For analytical purposes, Big-Data is to be considerable as a technically-minded challenge, for it to be stored, retrieved and collected. Thus, the dataset size should be minimized to a nominal manner for easy processing. The IECT lossy and lossless compression processes should be effective and efficient. This research was accomplished to expand compression of data techniques in a Big Data setting.

Additionally, the effective quality of image measurements is examined in the chapter in combination using the "Human Visual System" (HVS), along with associated factors. The results generated by the test application show that the compressed and reconstructed images computed by the method being proposed are satisfactory than alternate means of compression when it comes to the image quality and its compression ratio. The algorithm can select the final threshold value of the images inputted, providing optimal input for image compression, thus achieving a good result and providing satisfactory image quality.

5 Validation of Compression Quality

5.1 Overview

Digital images are prevalent in our daily lives and it is increasingly important to preserve these data. As previously mentioned, data compression has emerged as a possible solution through its capacity to reduce the size of the digital data (see Chapter 1). As such, data compression methods which are effective at reducing large data sizes and which can be stored in less space are required. Notwithstanding that the lossy compression method results in a high compression ratio, the quality of the output is generally satisfactory as discussed in Chapter 4. The compressed images when applied in object detection applications require algorithms like machine learning classifiers to assess the accuracy and performance to gauge the effect of compression. The purpose here is to compare the detection accuracy and performance of compressed images against uncompressed images. Thus, another detailed quantitative measure of the proposed compression algorithms can be used to validate its merits.

One of the most common approaches is the Feature-based detection methods which allow dimensional reduction of the datasets and then classify them into labels or classes. Generally, a 'feature' represents a larger amount of data/information into a much smaller sized representative which enhances the detection performance significantly. This chapter discusses feature extraction and classification using the Support Vector Machine (SVM) algorithm for 2D and 3D images with and without the use of proposed compression algorithms. The SVM algorithm is a widely applied machine learning technique with a high generalization capability which is applied in many supervised classification problems. Thus, the application of a machine learning algorithm in combination with the proposed enhanced wavelet methods provides an important and novel approach to test the compression quality. This work can lead to various further applications where reduced image size can prove vital.

5.2 Object Detection Experiment

The traditional approach for measuring the quality of the compressed images includes a comparison of pre and post compression images with different indices including SSIM, PSNR etc. This approach can be further enhanced by applying recent computational methods like dimensionality reduction and machine learning (Endert, A., Ribarsky, W., Turkay, C., Wong, B.W., Nabney, I., Blanco, I.D. and Rossi (2017)). The advantage of these methods is, they can assess the usefulness of the compressed images at much abstract level like in a feature form. The feature level handling of data provides far superior performance and can be used in many application domains (Hassaballah, M., Abdelmgeid, A.A. and Alshazly (2016)). In this experimental work an SVM classifier is applied over a set of features extracted from compressed and uncompressed images. Also, a range of data is created from a base image by adding various noise levels to simulate real life environmental conditions.

The SVM is a machine learning classification technique used for pattern recognition. The SVM is typically applied for the resolution of a multi-class classification problems where it splits the classes using a decision surface or a kernel. The decision surface is often referred to as the optimal hyperplane, with the support vectors being those data points nearest to the hyperplane. As such, the support vectors are crucial in the training set. The SVM may be modified into a function as a non-linear classifier via the utilization of non-linear kernels. Notwithstanding that the most basic function of the SVM is as a binary classifier, it may also function as a multiclass classifier through the combination of numerous binary SVM classifiers – this creates a binary classifier for every pair of classes. Pairwise classification strategies are generally used to achieve multiclass classifications. The SVM classification output reflects each pixel's decision value for each class and is utilized for probability estimations. Probability values signify 'true' probability in that the range of each probability is from 0 to 1, and the total amount of the values for each pixel is equal to 1. The classification is then made based on the selection of the highest probability.

Penalty parameters are also included in the SVM to allow for some degree of misclassification. This is especially important in relation to non-separable training sets. Penalty parameters control the trade-off taking place when permitting training errors and enforcing inflexible margins. This produces a soft margin that allows for some misclassifications (e.g. training points positioned on the incorrect hyperplane side). When the penalty parameter value is increased the misclassification cost is also increased forcing a more accurate model to be created with limited generalizability (Zhuo, L., Zheng, J., Li, X., Wang, F., Ai, B. and Qian (2008)). Several SVM classifier kernel functions are available including linear, polynomial, Radial Basis Function (RBF) and sigmoid. This study selected the linear kernel based on the belief that it functions effectively in most cases. The binary SVM supports the construction of a hyperplane set within an infinite spatial dimension that can subsequently be separated into two different representational forms such as the linear and non-linear SVM (Chao & Horng (2015)). Initially, a binary classification issue was considered, with the training data set formulated as follows at Equation 5.1:

$$T = \{(x_1, y_1), (x_2, y_2) ...... (x_l, y_l)\} \tag{5.1}$$

$$y_i \epsilon \{-1, 1\}, x_i \epsilon R^d$$

Where x_i represents the data point and y_i the corresponding designed label. The l signifies the number of training data set elements. The linear SVM locates the optimum division margin by resolving the optimization task as follows at Equation 5.2:

$$Minimize \left\{\frac{1}{2}|w|^2 + C\sum_{i=1}^{l} \varepsilon_i, \quad \varepsilon_i \geq 0\right. \tag{5.2}$$

$$Subject\ \ to\, y_i \left(w^T x_i + b\right) \geq 1 - \varepsilon_i,\ i = 1, 2, ...l \tag{5.3}$$

Where a penalty value is C, positive slack variables are ε_i, a normal vector is w, and a scalar quantity is b.

The SVM locates a linear dividing hyperplane that has the highest margin within the higher dimensional space,$C > 0$ represents the penalty parameter for the error. In addition, the Equation 5.4 below is labeled kernel function:

$$K(x_i, y_i) \equiv \varphi(x_i) T \varphi(y_i) \tag{5.4}$$

Where k is kernel function, x_i, y_i=n dimensional inputs. For kernel functions, the scalar product can be calculated between two points of data within a higher dimensional space while not generating an explicit calculation of the map from the space of input up to the higher dimensional space (Huang, S., Cai, N., Pacheco, P.P., Narandes, S., Wang, Y. and Xu (2018)).

This chapter demonstrates the use of machine learning as a method to evaluate data quality prior to and the following compression. There are two processes involved in the classification algorithm are as below:

1. **Feature classification without compression:** This process to create the dataset for the learning of classification algorithm where every noise will simulate real life environmental effects on images. In this case, will start with input selecting an images sample from larger datasets, followed by the preprocessing step will be resizing all images to one common size for correct comparison. Then adding some noise such as Salt Pepper, Gaussian etc. which can effect

the micro occlusion into images to represent the different environment condition. After that, extract features which allow dimensional reduction of the datasets (Kale, Anup and Chaczko (2015)), there are main features extracted for classification such as color descriptors, texture, edge count and blob count etc. Follow by classifying the features into labels as illustrated in Figure 5.1.

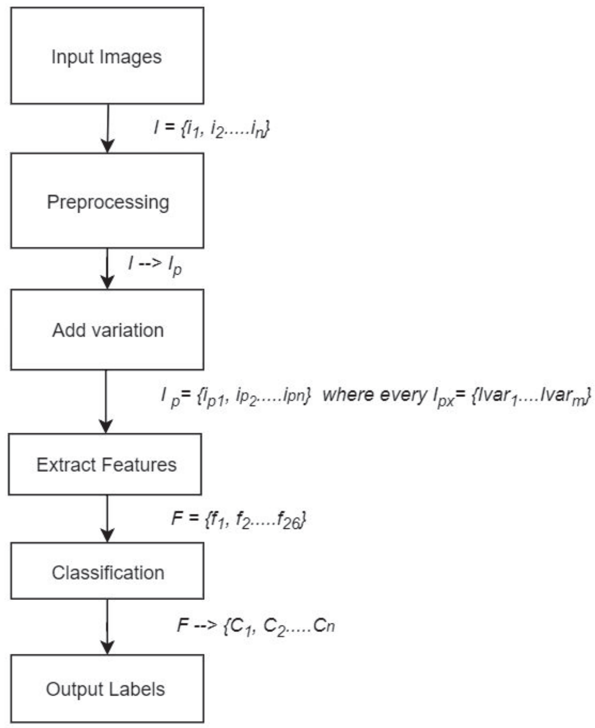


Figure 5.1: Feature classification without compression flowchart

2. **Feature classification with compression technique:** In this case, follow the same steps as explained above in the Figure 5.1 which is feature classification without compression but will be adding the compression algorithm from level to another level. Then will apply the feature extraction to assess the compressed image. At the end will classify these datasets into labels or classes as illustrated in Figure 5.2.

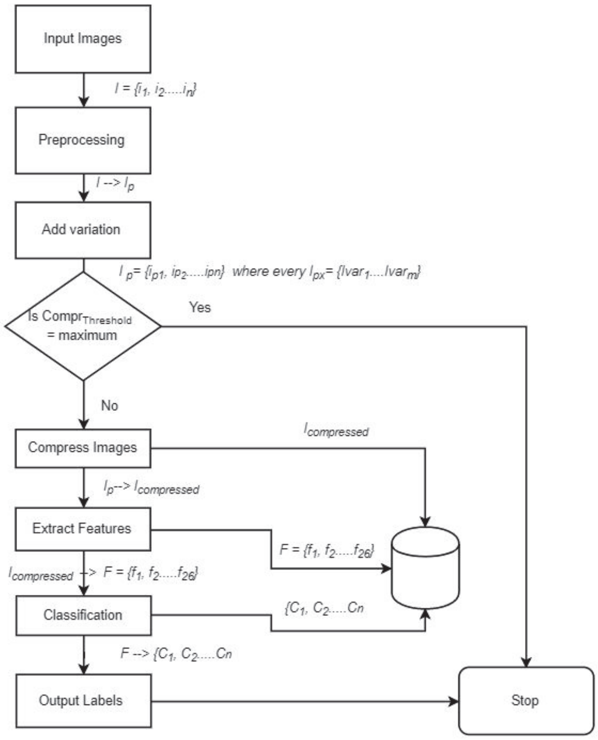


Figure 5.2: Feature classification with compression flowchart

In this chapter, outlines the process for extracting the input image features and then classifying them to obtain the output labels. Here, the features of the input image are extracted so that they may be compared to the compressed images to identify their differences. The compression technique can be used to support an initial reduction in the size of the data in order to transfer it more rapidly, then using machine learning to check how the images differ. Because a high capacity image is needed, data compression is a central component of this research.

5.3 Experiment Results

This section present experimental result for two training models for two different datasets (compressed and uncompressed images), includes 2 types of images 2D and 3D images as follows:

5.3.1 Experiment for 2D Images

In this case, every training model has two colour images will separate them into 35 for compressed and uncompressed images then add some noise to those images. In compression case will compress those images into different levels which have 70 compressed images for every level. The experimental work for 2D incorporates the following activities:

1. Add Variation (Noise) A noisy channel can introduce noise into the transmission medium leading to errors when measuring and when quantizing the data for digital storage. The image delivered to the receiving end must be processed prior to its use in additional applications.

Noise denotes unwelcome information that diminishes the quality of the image. Noise represents an arbitrary variation in image intensity and is observable as grains within the image. Noise results in the image pixels presenting diverse intensity values instead of the correct pixel values. Noise emerges due to the physical nature of the processes of detection, comes in diverse forms and has many causes. Noise is expressed as a process (n) affecting image (f) and is separate to the scene (initial signal-s). Therefore, the noise model may be expressed as following Equation 5.5:

$$f(i,j) = s(i,j) + n(i,j) \tag{5.5}$$

Numerous factors may be responsible for the introduction of noise into the image acquiring or transmitting an image. The extent to which the noise affects the image is dependent on the nature of the disturbance. Therefore, the type of noise must first be identified and then the different algorithms are applied for the removal of the noise (Kaur (2015)). The common noise types are:

- **Salt Pepper Noise:** refers to an impulse noise reflecting intensity spikes that occur as a result of data transmission errors. Specifically, salt and pepper noise manifests in the image due to sharp and sudden fluctuations in the image signal. Salt and pepper noise corrupted images result in the noisy pixels taking the maximum and the minimum values only within the dynamic range. For instance, the pepper noise value in an 8-bit image is typically 0; whereas the salt noise value is typically 255. Salt and pepper noise are mostly the result of a malfunction in the camera sensors pixel elements, a fault in the memory location function or errors of timing in the digitization process. The impulse noise present at following Equation 5.6:

$$p(z) = \begin{cases} p_a \ for \ \text{z=a} \\ p_b \ for \ \text{z=b} \\ \text{0 otherwise} \end{cases} \tag{5.6}$$

- **Gaussian Noise:** refers to noise with an even distribution over the signal whereby each pixel within the noisy image equals the total true pixel value in addition to an arbitrary Gaussian distributed noise value. Gaussian noise is not dependent on the intensity of the pixel value at every point. White Gaussian noise (named after white light) presents as a unique case however as the pixel values at any paired times have identical distribution and statistical independence. The main sources of Gaussian noise in a digital image emerge at the acquisition stage, such as sensor noise due to the inadequate illumination, elevated temperature or transmission. The Gaussian noise present at following Equation 5.7:

$$p(z) = \frac{1}{\sqrt{2\pi\sigma}} e^{-(z-\mu)^2/2\sigma^2} \tag{5.7}$$

- **Speckle Noise:** refers to multiplicative noises which contrast to Gaussian noise and salt and pepper noise. Speckle noise is modelled according to arbitrary value multiplications of the image pixel values and is expressed as Equation 5.8:

  $$p = I + n * 1 \tag{5.8}$$

  Where p represents speckle noise distribution, I represents input image and n represents uniform noise according to mean 'o' and variance 'v'. Speckly noise diminishes both active radar image quality and Synthetic aperture radar (SAR) image quality. The noise manifests due to the back scattered signals are coherently processed at multiple distribution points (Mansourpour, M., Rajabi, M.A. and Blais (2006)).

- **Poisson or shot photon noise:** refers to noise caused by an inadequate number of photons being detected by the sensor. This means the statistical information detected is insufficient. Shot noise is possible because light and electric currents comprise the movement of distinct packets. Shot noise may dominate as a result of the finite number of particles carrying energy being sufficiently small to create significant uncertainties around the incidence of random independent events (i.e. the Poisson distribution). The magnitude of shot photon noise increases in relation to the average magnitude of the light's current or intensity.

In this case, step one – Preparing the dataset by adding noise to the images to signify different environmental conditions as shown in Figure 5.3. If image present noise at very high level that means a high level of compression required to apply.

2. Compression at Different Levels for 2D Images In this experiments will use SVM to evaluate the quality of compression techniques coefficients applies wavelet regression. Regarding image compression, two different solutions are typically considered: lossless and lossy (see Chapter 2). Lossy compression techniques typically rely on the transformation of a spatial image domain into a domain. This

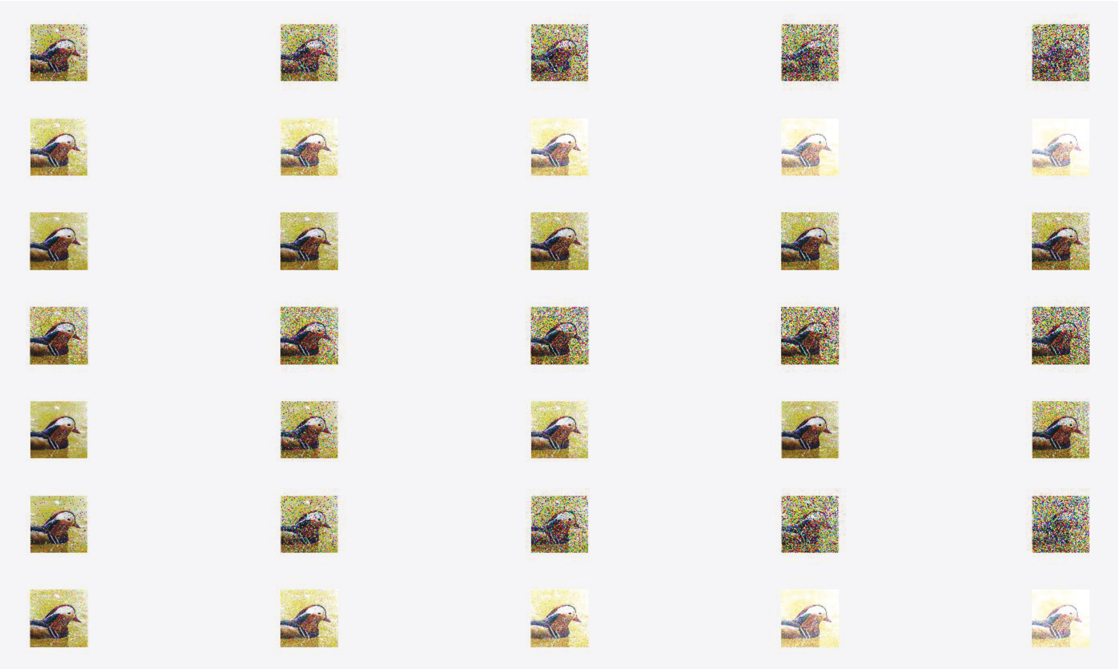


Figure 5.3: Different variation results

exposes the components of an image based on their relevance and allows coding methods to be employed to suppress redundant data as explained in Chapter 4. Discrete wavelet transforms (DWT) is then applied at different levels to generate a multi-scale image decomposition. Using filters and sub sampling methods, a decomposed image is produced which is effective at exposing the different scales of data redundancy. The application of a coding principle is then undertaken for the compression of the data at different levels. Following this process, the differences between the original image and the compressed image are measured using machine learning such as: accuracy, Bits Per Pixel (BPP), Structural Similarity (SSIM) Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), and performance.

The planned image compression is initially applied to 2D colour images using DWT. Both the original and compressed images are utilized to measure performance and accuracy. The outcomes provide different compression ratio values and bits per pixel (bpp) for 49 different compression levels as illustrated in Figure 5.4. This process is then followed by the use of the SVM with the linear kernel to show the different outcomes for the two images.

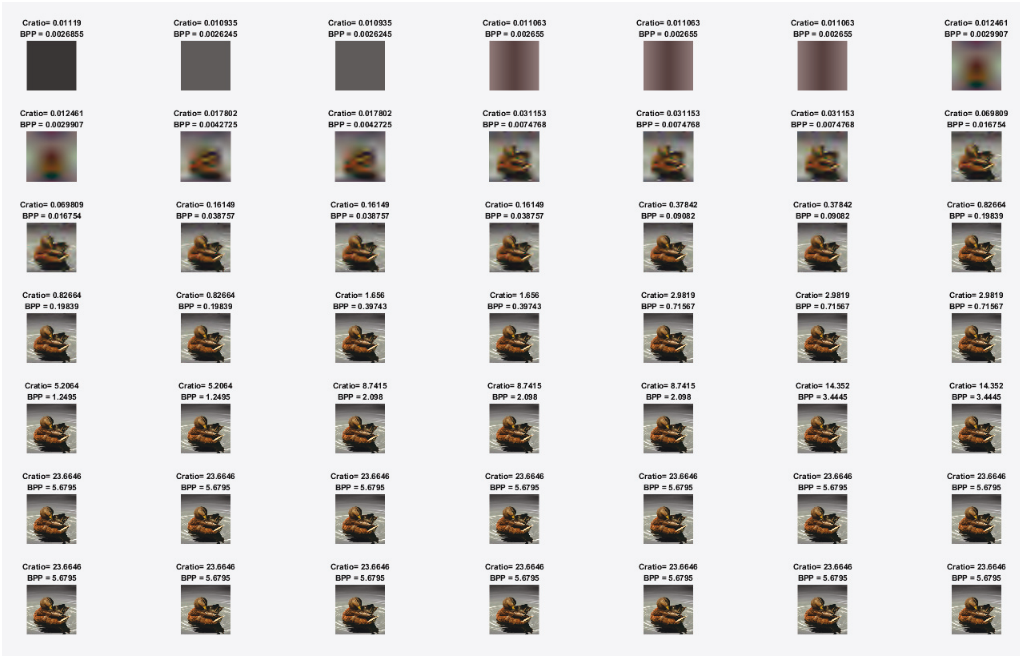
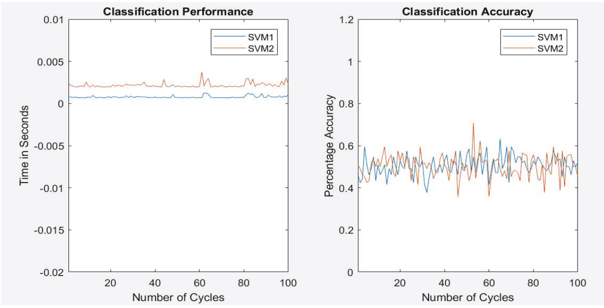
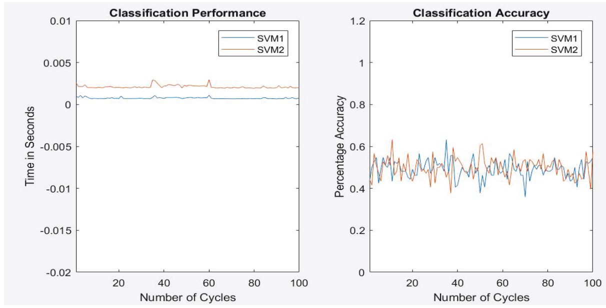


Figure 5.4: Compressed images for 49 different levels

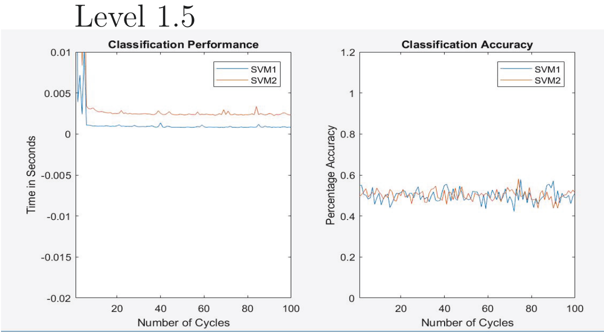
3. Classification for 2D Images Support Vector Machines (SVM) refer to the classification system emergent from statistical learning theory. This system is applied with success in different fields including the categorization of texts and the classification of images, for recognizing hand-written characters, analyzing bio-sequences, and for image compression, etc. Regarding computer vision applications, a 'feature' is defined as the entity carrying valuable data. An object in the image may be defined by one or more features. The features most often used are in the spatial domain including points, edges, or shapes; or in the spectral domain including colour and shape spectral descriptors. In terms of real-time performance and to reduce the overall costs of computation, the decision was made to process the interest points. Regarding the feature extraction technique, the blob detection algorithm was utilized to acquire the colour pixels sampled relative to the focus region's length and width (Kale, Anup and Chaczko (2015)). This section demonstrates a practical application of the results to classify an image on data that has been encrypted with data compression methods as illustrated in Figure 5.5 and Figure 5.6.



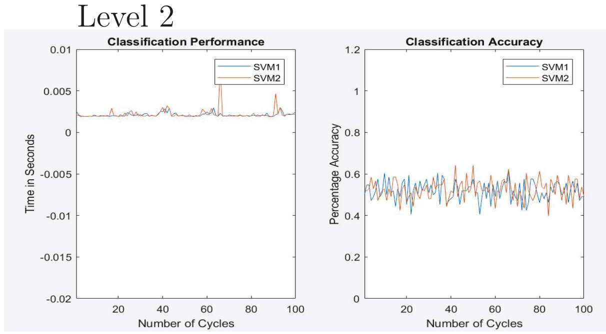
Level 1.5



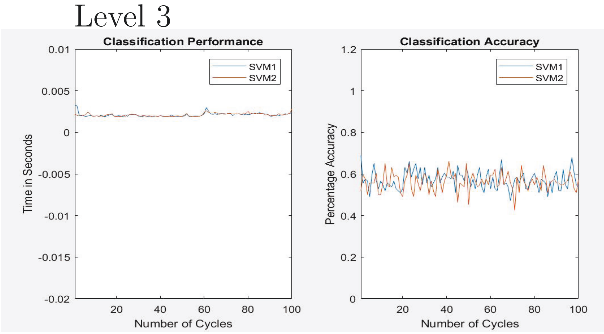
Level 2



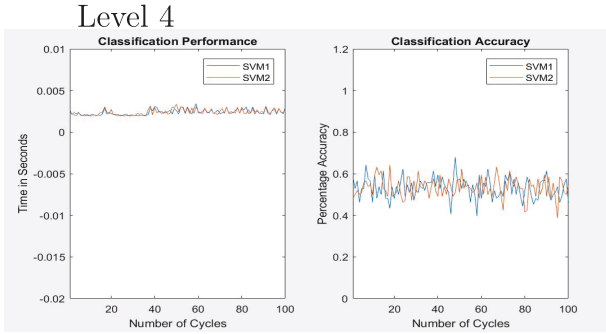
Level 3



Level 4



Level 5



Level 6

Figure 5.5: 2D Classification results for different compression levels

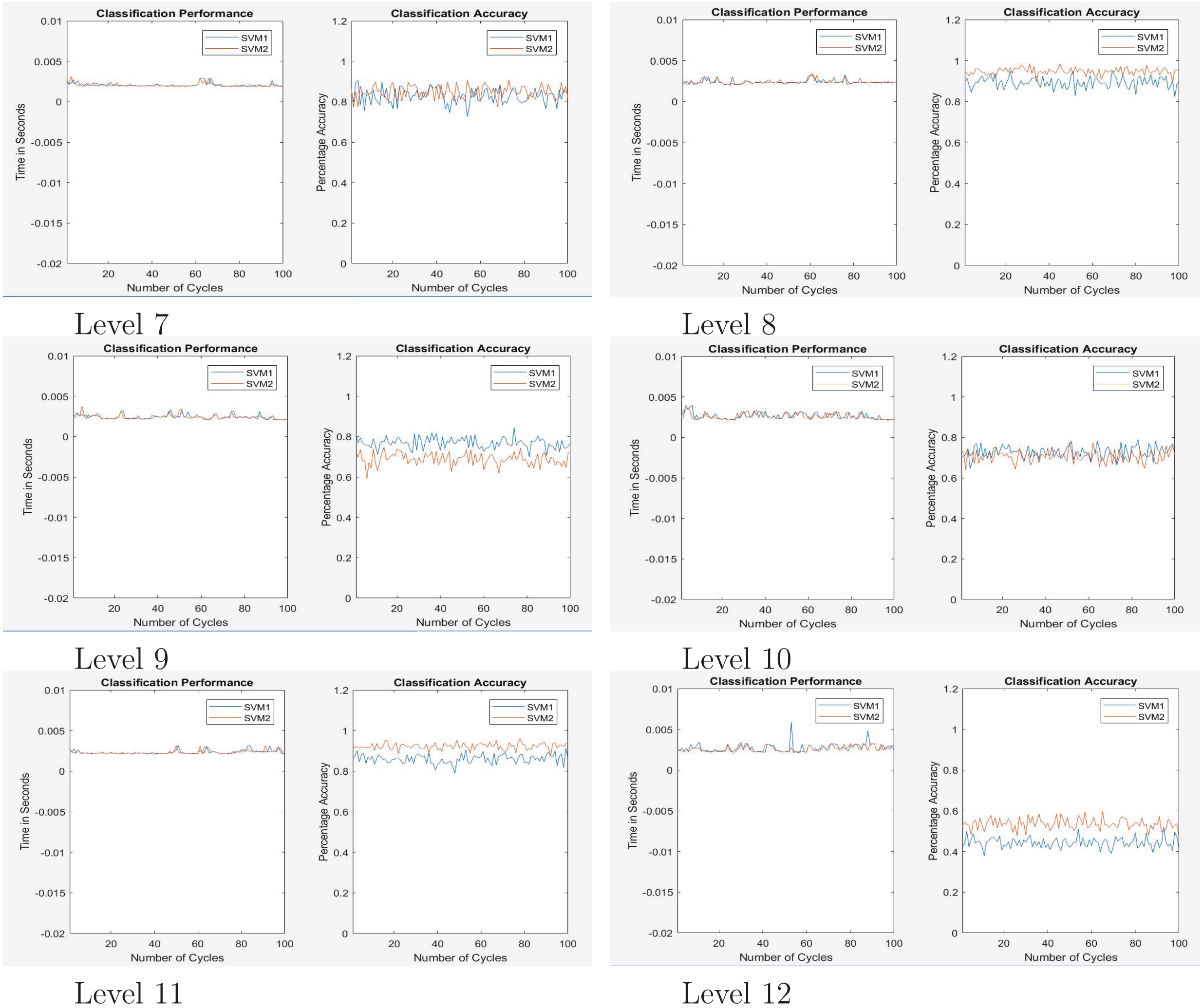


Figure 5.6: 2D Classification results for different compression levels

Table 5.1 demonstrates the compression quality measurement for two training models drawing on two different sets of data. Column 1 in the Table 5.1 specifies the level of compression from highest to lowest levels. Columns 2 and 3 indicate the average values of BPPs and compression ratio representing the size of the compressed images. Column 4 and 5 shows the overall image quality measurements with different indices including SSIM and PSNR. In Table 5.2 demonstrates the performance and accuracy measurement of the SVM classification algorithm for pre and post compression images. Column 2 and 3 in Table 5.2 indicate the average values of the performance before and after compression. Last two columns indicate the average values of the accuracy before and after compression. The results show that after the compression algorithm the accuracy and performance demonstrated only a marginal level of change.

Compression Percentage Value	BPP	Compression Ratio	SSIM	PSNR
2	0.002584	0.01076653	0.221376897	14.5717367
3	0.002584	0.01076653	0.230019626	15.23875221
4	0.0026027	0.010844639	0.259844396	16.20835662
5	0.0024719	0.010299683	0.287766783	16.95449296
6	0.0033454	0.013939085	0.304781718	17.83559302
7	0.0050443	0.021018074	0.327177522	18.65275601
8	0.0098646	0.041102455	0.356623072	19.39380225
9	0.0098646	0.041102455	0.386912874	20.08823871
10	0.4923981	2.05165863	0.494141574	21.15446072
11	1.8658094	7.774205889	0.668946233	23.2098975
12	1.8658094	7.774205889	0.908799332	30.73400946

Table 5.1: Performance parameters results for 2D images

Compression Percentage Value	Average Performance Compressed image (Seconds)	Average Performance Uncompressed image (Seconds)	Average Accuracy Compressed image (%)	Average Accuracy Uncompressed image (%)
2	0.001240209	0.003378808	0.493079365	0.503619048
3	0.000941783	0.00244802	0.500730159	0.498031746
4	0.002112135	0.002199647	0.518301887	0.524528302
5	0.002100939	0.002103189	0.571132075	0.561226415
6	0.002394397	0.00238872	0.530943396	0.533679245
7	0.002069497	0.002051376	0.828113208	0.848018868
8	0.002393294	0.002381446	0.893485714	0.947542857
9	0.002432667	0.002412663	0.768235294	0.688823529
10	0.002332612	0.002323447	0.860119048	0.922301587
11	0.002912069	0.002425057	0.856113744	0.855165877
12	0.002287262	0.00222645	0.576031746	0.537142857

Table 5.2: Performance and accuracy comparison results between (compressed and uncompressed images) for 2D images

5.3.2 Experiment for 3D Images

In this case, in 3D one image has 27 frames of 2D pixel arrays will add 35 noises for each and every one. In compression case will have 54×35 images will be compressed into different levels which have 1890 compressed image for every level. The rationale behind selection only 6 to 11 compression levels in this case is:

1. Too much of compression makes image visibility to lose. In the 3D compression being a biomedical image used for the experimental work the visibility aspect is very important. That's why compression level 6 onwards was assessed.

2. Minimum Compression: Level 11 onwards the compression effects do not make any substantial effect on the image SSIM, MSE, PSNR etc. The experimental work for 3D incorporates the following activities:

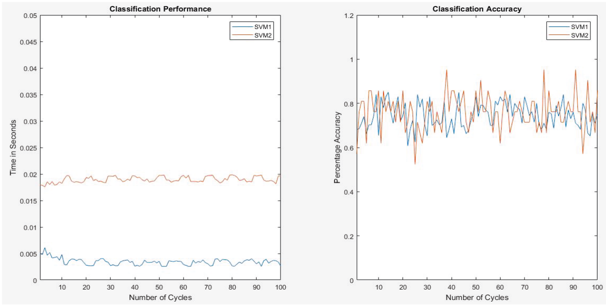
1. Add Variation (Noise) In this step will follow the same as the 2D images for more details see section (5.3.1).

2. Compression at Different Levels for 3D Images Three-dimensional (3D) images comprise several images or image sequences taken at different cross sections resulting in very high volumes of data. An increase in the data amount leads to an increase in the size of the data for storage. Data compression is integral to reducing the amount of data for storage. In addition, because medical images are achieved at the expense of radiation exposure, the image must be maintained for an extended time period. An increase in the volume of data for storage increases the demand for compression methods. Data compression is thus needed for data preservation as well as for the efficient use of the bandwidth for transmission.

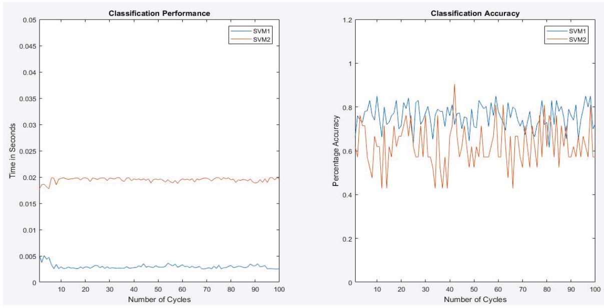
Justification for the introduction of 3D reconstruction emerges from the desire to use new metrics for error measurements and due to the perceived benefits of 3D visualization for assessing compression algorithm quality. Regions of diagnostic significance including cancer, lesions and the brain are unable to tolerate high compression ratios leading radiologists to opt for lossless compression methods for such regions; whereas, lossy compression methods are reserved for the outer regions (Banu, N.M. and Sujatha (2015)). Figure 5.7 present the 3D image in Tagged Image File Format (TIFF) which contains the 27 frames of 2D pixel arrays.

Figure 5.7: 3D original images

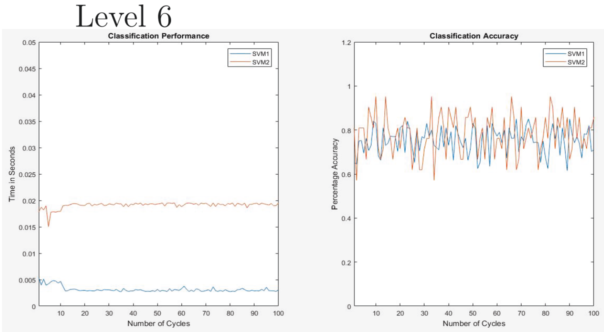
3. Classification for 3D Images In this research 3D image has 27 of the 2D images which is the size will be 256 × 256 ×27, that means will dealing with 1,759,472 pixels. Firstly, will start to compress every frame at a different level then will classify to measure the differences for accuracy, performance and quality for every level. This section demonstrates a practical application of the results to classify a 3D image on data that has been encrypted with data compression methods as illustrated in Figure 5.8.



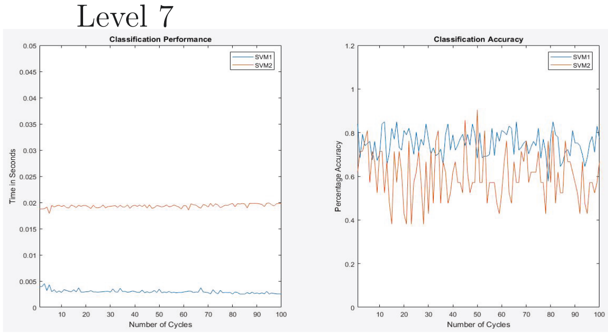
Level 6



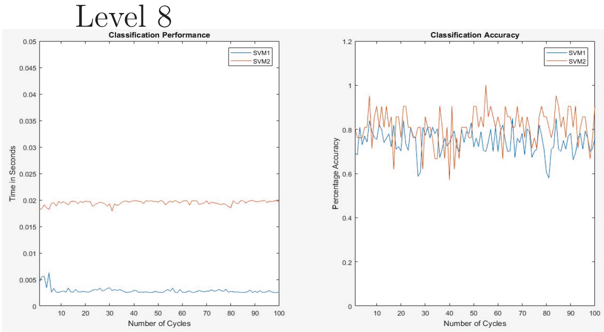
Level 7



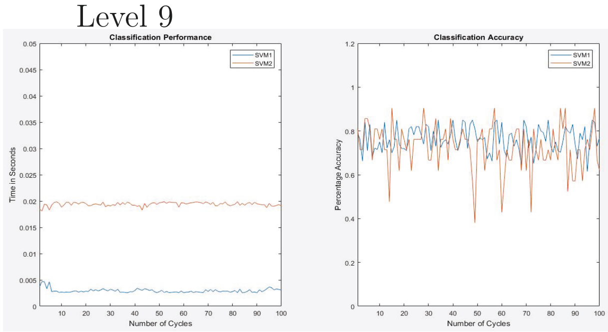
Level 8



Level 9



Level 10



Level 11

Figure 5.8: 3D Classification results for different compression levels

Table 5.3 illustrate the measurement of compression performance from two training models for two different datasets. The first column in Table 5.3 indicates the compression levels from the highest to lowest levels. Second and third columns show BPPS and compression ratio which present the size of compressed images. Then the next three columns show the overall image quality measurements with different indices including SSIM, PSNR and MSE. Table 5.4 demonstrates the performance and accuracy measurement of the SVM classification algorithm for pre and post compression images for 3D images. First column shows the compression level from level 6 until level 11. Column 2 and 3 indicate the average values of the performance before and after compression. Last two columns indicate the average values of the accuracy before and after compression. The results show that on level 11 which is the minimum compression does not make any substantial effect on the image SSIM etc.

Compression Percentage Value	BPP	Compression Ratio	SSIM	PSNR	MSE
6	17.00866699	212.6083374	20.01938841	19504.53412	2552014.03
7	67.35021973	841.8777466	66.83754989	20378.73743	2238971.059
8	396.4436035	4955.545044	254.6169509	22218.68106	1227234.528
9	976.2651367	12203.31421	435.980288	25053.22584	549313.1076
10	1822.9375	22786.71875	633.3266698	28860.59388	239694.8511
11	2865.38916	35817.3645	790.3181122	33507.21743	83128.23307

Table 5.3: Performance parameters results for 3D images

Compression Percentage Value	Average Performance Compressed image (Seconds)	Average Performance Uncompressed image (Seconds)	Average Accuracy Compressed image (%)	Average Accuracy Uncompressed image (%)
6	0.0081	0.0037	0.6186	0.7533
7	0.0049	0.0038	0.6295	0.7646
8	0.0036	0.0036	0.6814	0.7477
9	0.0038	0.0040	0.7447	0.7648
10	0.0035	0.0038	0.7473	0.7838
11	0.0036	0.0037	0.7416	0.7671

Table 5.4: Performance and accuracy comparison results between (compressed and uncompressed images) for 3D images

5.4 Summary

The evolution of 3D medical image compression 2D compression using machine learning was discussed. Compressed images must be diagnostically lossless and have a reduced bandwidth to ensure the quality of the image. The SVM algorithm, is a powerful and flexible machine learning technique adopting the kernel method for data representation. This chapter explores SVM with the linear kernel to use with wavelet compression methods for binary classification purpose. The 2D classification results did show the marginal difference in accuracy and performance when an image was compressed and used as it is. It is very encouraging to see that at maximum compression level the accuracy difference was observed up to 13.5% (less for the compressed image). Whereas, the performance mostly remained the same since the number of features extracted and classified in both cases were the same. In the case of the 3D classification, the performance was seen in comparable range or very similar. Whereas, the accuracy was seen relatively less than (by 15% approximately) than 2D classification due to the massive size of the imagery. The 3D classification accuracy can be enhanced further by using either feature optimization techniques (to reduce redundancy at feature set) or by using a learning intensive classification technique like Artificial Neural Networks or Deep Learning. Here, an attempt was given to conduct a primary investigator for comparison purposes only. Hence, the SVM classification was mainly used to compare accuracies with and without compression. The goal here was not to improve detection accuracy and was to compare accuracies only. In future, the Deep learning approach will be used to improve accuracy to a maximum.

6 Action Research

6.1 Overview

Due to the increased data volume being produced for various heterogeneous sources - the processing, real-time transfer, maintenance and storage of big data is reaching a significant scale. In many cases, the information contains redundant and irrelevant data that can be eliminated to make the file size more managed. Variations in techniques can achieve such an exercise, known as data compression techniques. The techniques can be applied to video, audio, images, text and image data. They are compressing the data aids to increasing speed of transfer, but also the field of knowledge discovery and time of processing. Data compression - particularly for images -plays a very crucial role in the field of multimedia computer services and other telecommunication applications. This chapter presents some action studies of data compression methods can provide effective solutions to problems related to stitching large size images, big data storage based on DNA computing, survey to evaluate the subjective quality and data compression using steganography.

These action studies of data compression methods as follows:

- 3D Stitching Image using Compression Technique
- Big Data Storage based on DNA Computing
- Subjective Quality Evaluation (Survey)
- Data Compression using Steganography

6.2 3D Stitching Image using Compression Technique

Image stitching involves combining two or more images which have sections that overlap to produce a single high-resolution or panoramic image. The software required for image stitching may be purpose-built, included in a suite of photo editing features, or be included as a camera function. Image stitching allows multiple camera images to be combined to produce a larger image with a ratio and resolution (super resolution) that is bigger than that of a normal single camera image. This technology allows wide shots to be positioned without copied objects or distortion

(Schmitz, A., Li, M., Schönefeld, V. and Kobbelt (2014)). To achieve optimal results when image stitching, the overlapping of images must be relatively precise, and the exposure settings must be identical. In addition, algorithms are needed to create a composite surface, align pixels, align images and to recognize distinctive features to function as points of reference for the software to achieve accurate alignment. This is shown in the following Algorithm 6.1. Image stitching is both an intensive and a complex process, and expensive to complete. Extensive literature is available on the image stitching process, and several months is needed for its implementation. OpenCV (OpenCV homepage. http://opencv.org/.) is an open-source toolkit available to users to assist with overcoming any number of computer vision issues. The toolkit includes an integrated stitcher to produce panoramas that can be applied with limited configuration problems. Figure 6.1 outlines the process used by OpenCV to stitch the input image to a single panorama.

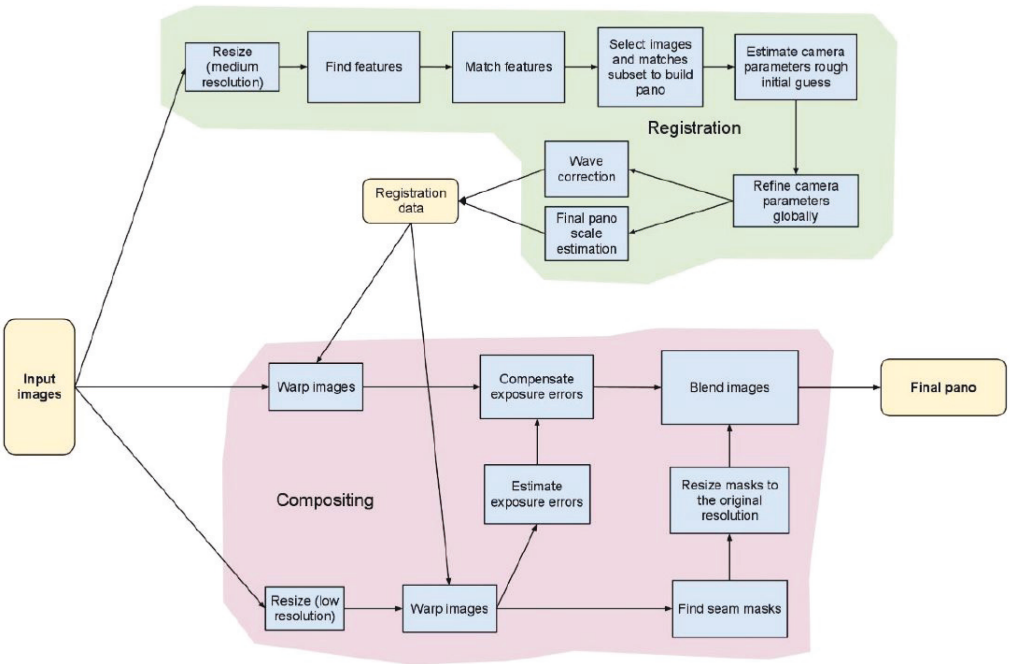


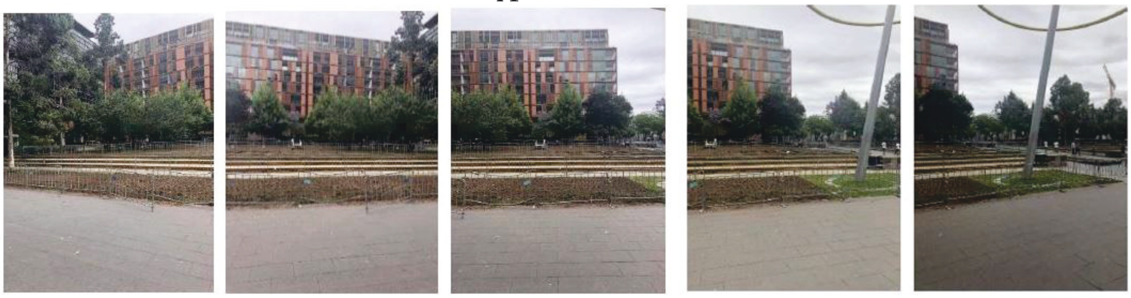
Figure 6.1: OpenCV stitching pipeline flowchart (Schmitz, A., Li, M., Schönefeld, V. and Kobbelt (2014))

Algorithm 6.1 Performing image stitching

```
images [] < −− Input images
Assuming, that the center image is no_of_images/2
let centerIdx = length(images)/2
for each images [] at positions 0− >centerIdx :
perform leftward stitching
for each images [] at positions centerIdx − > length (images): perform rightward stitching
```

To test this tool will have 4 sets of images which contain 4-7 images as shown at Figure 6.2, then try to stitch those images to pano as present at Figure 6.3. Comparing the size of the original imagery and the output size as shown at Table 6.1. Table 6.1 shows the stitched size is larger than the original image size. Because of the constraints from the images by phone. The smartphone will automatically adjust the spotlights when taking images, those images taken from different directions will lead the dark part for the stitched image which could increase the expected size.

A



B

C

D

Figure 6.2: Various sets of original images

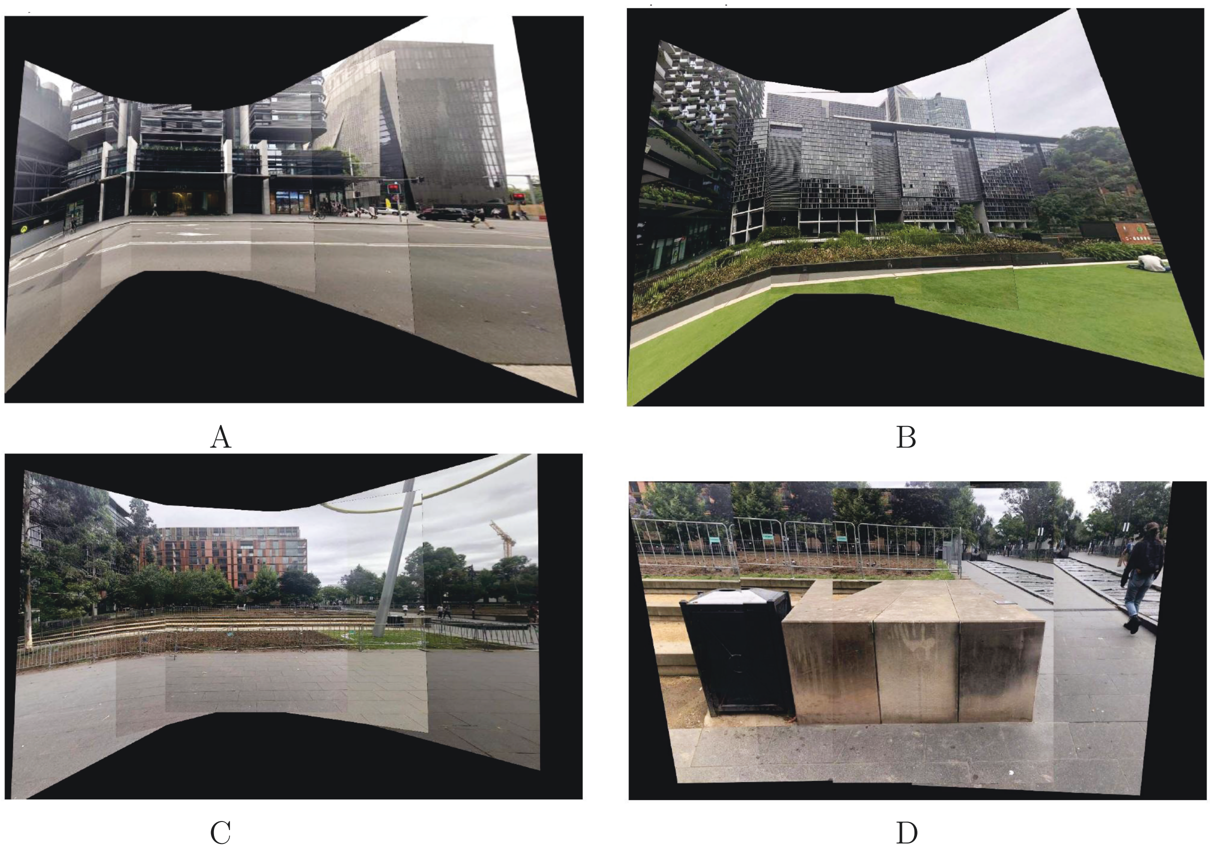


Figure 6.3: Stitching Various sets of original images

No.	Name	Number of Images	Original image size (KB)	Stitched images size (KB)
1	Example A	7	1110	1540
2	Example B	5	1000	1003
3	Example C	5	1210	1330
4	Example D	4	865	887

Table 6.1: Result of the original and stitched images size

6.2.1 Image Stitching Scenario

Because the size for stitching images increase the compression technique require to reduce this size to be easy store and transmit through the internet. The main aim of stitching images is to reduce the large size of stitching images with high resolution to store it in less space. In this case, will start capturing the four (4) different scenes using 360-degree images which randomly taking. For those images will use the same process which is (Stitch and Compress). Then record the result for the fourth different group of images without affecting the result will keep using the same stitch and compressed tool. Figure 6.4 explain the image stitching strategy.

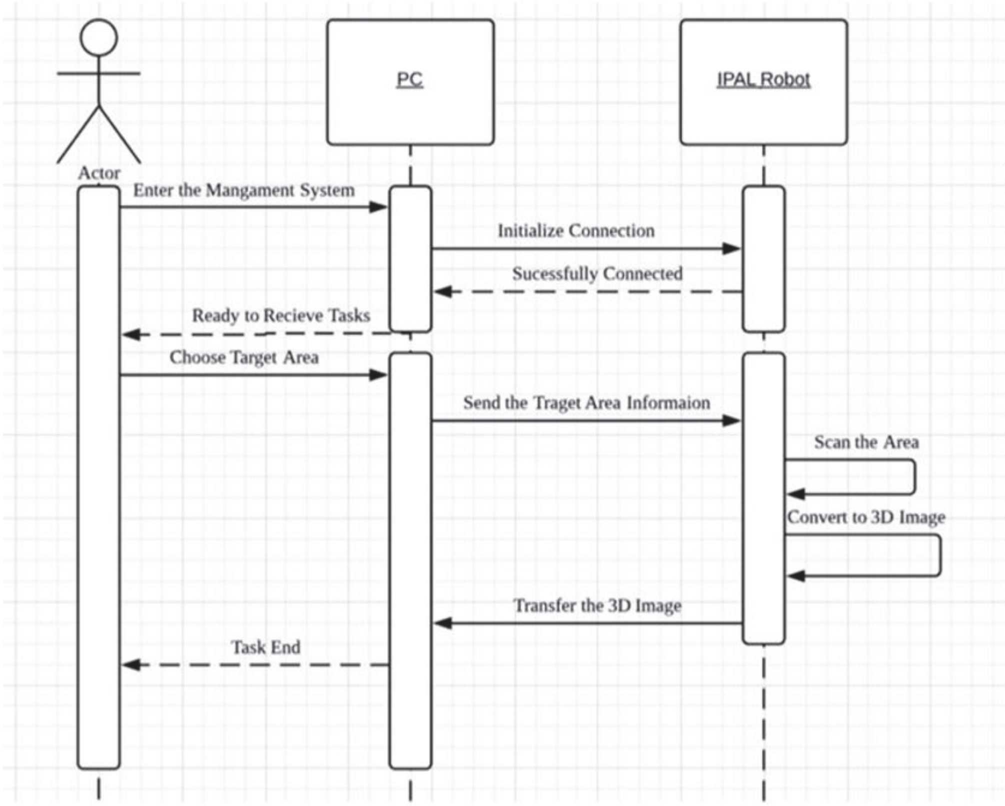


Figure 6.4: Image stitching scenario

This action study will have two different ways to test the results includes as follows:

- **Group 1:**

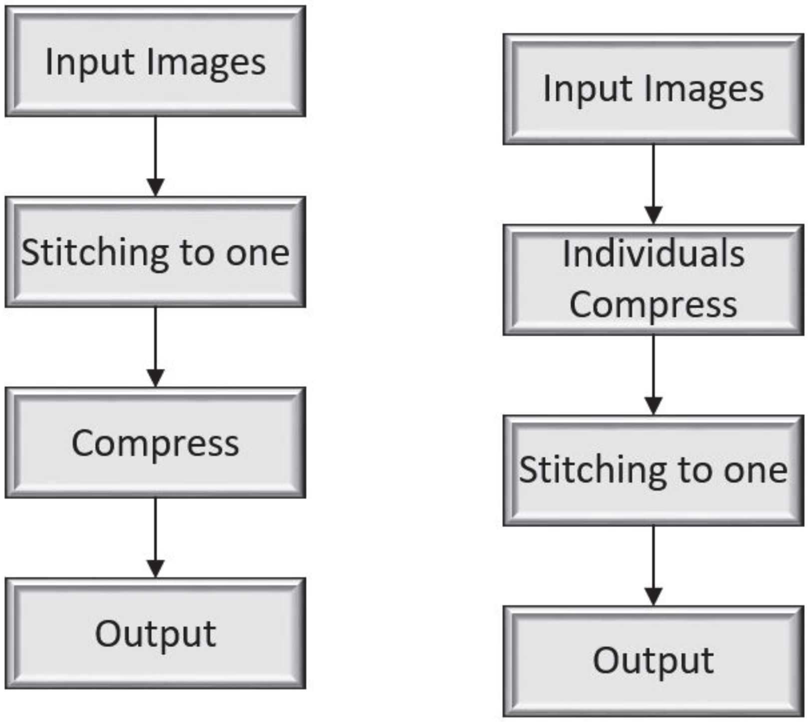
In this scenario will take a group of images (around 15 images) such as Shopping Mall or Woolworth and try to stitch them, then compress the output as shown at Figure 6.5a. The following steps incorporate group 1 activity:

1. Start input original images around 15 images.
2. Then stitched this 15 images together.
3. After that compress the stitch images as one image.
4. Finally get the compressed stitched images.

- **Group 2:**

Also in this scenario will take a group of images (around 17 images) such as Shopping Mall or Woolworth and try to compress every single image individually, then stitch them to get the compressed stitched images as shown at Figure 6.5b. The following steps incorporate group 2 activity:

1. Start input original images for example around 17 images.
2. Then compress every single image individually.
3. After that stitched these 17 compressed images together to be as one image.
4. Finally get the compressed stitched images.



(a) Group 1 flowchart (b) Group 2 flowchart

Figure 6.5: Group 1 and 2 flowchart

6.2.2 Image Stitching Results

The power of the compression techniques and the multimedia toll is clearly shown in this case study which is a successful implementation of the goal of this research. In this section 4 cases of stitching image includes:

- Shopping Mall A,
- Shopping Mall B,
- Woolworth A and
- Woolworth B.

First Case Shopping Mall A:

In this case, will have a capture of 15 images for Shopping Mall A took it from different angles. Then will be applied the Group 1 and Group 2 to compare those results to see the differences between the stitching images before and after compressed. Figure 6.6 shows the stitched image for all 15 images together for shopping mall A.

Figure 6.6: Stitched image for Shopping Mall A

Table 6.2 indicate that the compression technique could smaller the size of individual images in an average 1.76 ratio.

Image Number	Original Image Size (KB)	Compressed Image Size (KB)	Compressed Ratio
1	140	79	1.77
2	173	100	1.73
3	154	89	1.73
4	156	92	1.70
5	168	100	1.68
6	152	90	1.69
7	129	74	1.74
8	109	59	1.85
9	88	44	2.00
10	103	52	1.98
11	131	72	1.82
12	139	82	1.70
13	148	87	1.70
14	138	79	1.75
15	115	62	1.85
Total	2043	1161	1.76
Average	136.2	77.4	1.76

Table 6.2: Individual compressed ratio for Shopping Mall A

Table 6.3 shows that Group 1 and Group 2 have distinctive compression ratio, the ratio from Group1 nearly reach 5.2 times smaller size than original image size, Group2 only grain around 1.6 times smaller size.

No.	Name	Number of Images	Original Image Size	Compressed Image Size	Stitched Size (KB)	Compressed Size (KB)	Compressed Ratio
1	Group 1	15	2043	//	1380	395	5.17
	Group 2	15	2043	1161	1300	//	1.57

Table 6.3: Compare between Group1 and Group2 (Shopping Mall A)

Second Case Shopping Mall B:

In this case, will have a capture of 17 images for Shopping Mall B took it from different angles. Then will be applied the Group 1 and Group 2 to compare those results to see the differences between the stitching images before and after compressed. Figure 6.7 shows is the stitched image for all 17 images for Shopping Mall B, there is the Table 6.4 below shows the detailed description of the source images.

Figure 6.7: Stitched image for Shopping Mall B

Table 6.4 indicate that the compression technique could smaller the size of individual images in an average 1.77 ratio.

Image Number	Original Image Size (KB)	Compressed Image Size (KB)	Compressed Ratio
1	127	72	1.76
2	145	86	1.69
3	156	96	1.63
4	165	99	1.67
5	168	103	1.63
6	126	75	1.68
7	125	73	1.71
8	115	68	1.69
9	110	64	1.72
10	107	59	1.81
11	93	49	1.90
12	107	58	1.84
13	95	51	1.86
14	130	76	1.71
15	142	84	1.69
16	169	99	1.71
17	242	99	2.44
Total	2322	1311	1.77
Average	136.59	77.12	1.77

Table 6.4: Individual compressed ratio for Shopping Mall B

Table 6.5 shows that Group 1 and Group 2 have distinctive compression ratio, the ratio from Group1 nearly reach 6 times smaller size than original image size, Group2 only grain around 2.1 times smaller size.

No.	Name	Number of Images	Original Image Size	Compre ssed Image Size	Stitched Size (KB)	Compre ssed Size (KB)	Compre ssed Ratio
1	Group 1	17	2322	///	1210	368	5.92
	Group 2	17	2322	1311	1100	///	2.11

Table 6.5: Compare between Group1 and Group2 (Shopping Mall B)

Third Case Woolworth A:

In this case, will have a capture of 15 images for the Woolworth A took it from different angles. Then will be applied the Group 1 and Group 2 to compare those results to see the differences between the stitching images before and after compressed. Figure 6.8 shows the stitched image of Woolworth A for all 15 images together. The Table 6.6 indicate that the compression technique could smaller the size of individual images in an average 1.75 ratio.

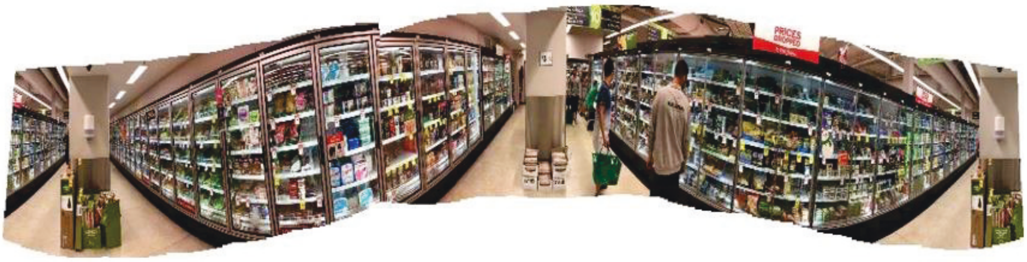


Figure 6.8: Stitched image for Woolworth A

Image Number	Original Image Size (KB)	Compressed Image Size (KB)	Compressed Ratio
1	242	150	1.61
2	241	147	1.64
3	246	155	1.59
4	203	123	1.65
5	193	116	1.66
6	203	123	1.65
7	235	144	1.63
8	234	146	1.60
9	236	147	1.61
10	224	138	1.62
11	213	129	1.65
12	195	118	1.65
13	179	106	1.69
14	200	120	1.67
15	228	141	1.62
Total	3500	2003	1.75
Average	233.33	133.53	1.75

Table 6.6: Individual compressed ratio for Woolworth A

Table 6.7 shows that Group 1 and Group 2 have distinctive Compress Ratio, the ratio from Group1 nearly reach 4.7 times smaller size than original image size, Group2 only grain around 1.8 times smaller size.

No.	Name	Number of Images	Original Image Size	Compressed Image Size	Stitched Size (KB)	Compressed Size (KB)	Compressed Ratio
1	Group 1	15	3500	///	2320	751	4.66
	Group 2	15	3500	2003	1900	///	1.84

Table 6.7: Compare between Group1 and Group2 (Woolworth A)

Fourth Case Woolworth B:

In this case, will have a capture of 13 images for the Woolworth B took it from different angles. Then will be applied the Group 1 and Group 2 to compare those results to see the differences between the stitching images before and after compressed. Figure 6.9 shows the stitched image for all 13 images together for Woolworth B. The Table 6.8 indicate that the compression technique could smaller the size of individual images in an average 1.63 ratio.

Figure 6.9: Stitched image for Woolworth B

Image Number	Original Image Size (KB)	Compressed Image Size (KB)	Compressed Ratio
1	302	186	1.62
2	302	188	1.61
3	271	166	1.63
4	224	132	1.70
5	197	115	1.71
6	207	125	1.66
7	241	149	1.62
8	237	146	1.62
9	200	123	1.63
10	202	124	1.63
11	284	178	1.60
12	230	143	1.61
13	253	158	1.60
Total	3150	1933	1.63
Average	242.31	148.69	1.63

Table 6.8: Individual compressed ratio for Woolworth B

Table 6.9 shows that Group 1 and Group 2 have distinctive Compression Ratio, the ratio from Group1 nearly reach 3.23 times smaller size than original image size, Group2 only grain around 1.17 times smaller size.

No.	Name	Number of Images	Original Image Size	Compressed Image Size	Stitched Size (KB)	Compressed Size (KB)	Compressed Ratio
1	Group 1	13	3150	///	3020	974	3.23
	Group 2	13	3150	1933	2700	///	1.17

Table 6.9: Compare between Group1 and Group2 (Woolworth B)

In this case, the result that found it from Woolworth B could be a bad experiment. Due to the constraints from manually image taking, the blank space for this one is too big to show the right size of the stitched image. But anyway, it could still indicate the rule how Group 1 performs better than Group2. It can even be used to prove the conclusion.

6.2.3 Summary

This chapter demonstrated how data compression methods can provide effective solutions to problems related to stitching large size images. A comparison of four different scenarios was undertaken to determine the effectiveness of their compression techniques for stitching images. The two main parameters for measuring the effectiveness applied in this study were compression ratio and compression quality. For all four scenarios, the compress ratio for each image is defined as the standard measure for determining compression quality, based on Original size / Compressed size. The Table 6.10 displays the results produced for each scenario. 'Compressed ratio for group 2' shows group 2 efficiency (first compress, then stitch). If Woolworths B is removed as an example, it is evident that stitching each of the compressed pictures would be of no benefit. It requires too much and cannot deliver adequate optimization.

Name	Average Compression Ratio for Individual Images	Compressed Ratio for Group 2
Shopping Mall A	1.76	1.57
Shopping Mall B	1.77	2.11
Woolworth A	1.75	1.84
Woolworth B	1.66	1.17

Table 6.10: Compression ratio for individual images

The images at Figure 6.10 shows that the compression among original, Group 1 and Group 2 output.

The three images have clearly been zoomed in multiple times and demonstrate a similar quality to that provided by human eyes. In regard to achieving a similar quality level, Group 1 is arguably the best choice for a small size (368 Kb) image. The compress ratios for Group 1 and Group 2 are compared at Table 6.11.

Name	Compression Ratio for Group 1	Compressed Ratio for Group 2
Shopping Mall A	5.17	1.57
Shopping Mall B	5.92	2.11
Woolworth A	4.66	1.84
Woolworth B	3.23	1.17

Table 6.11: Comparison between Group 1 and Group 2

Thus, when producing similar quality images, Group 1 is consistently more efficient than Group 2. That is, the images should be managed in the following way to produce more efficient outcomes: use original images to produce a stitched image and then compress the stitched image. If the Woolworth B example is removed, the average compression ratio is around five, meaning it has the potential to save five times the amount of time than when applying the traditional method.

(a) Original image size (1210 KB)

(b) Group 1 compressed image size (368 KB)

(c) Group 2 compressed image size (1100 KB)

Figure 6.10: Quality of images

6.3 Big Data Storage based on DNA Computing

The review paper "Big Data Storage based on DNA Computing" which was published in APCASE 2015 conference reviewed there is a necessity of notable scaling down in the informational approach being saved in recent years. The work describes the advantages, with the increase in the effective ability to claim data manageability, as well as improving the information entrance distribution. For engineered DNA, it widens the potential possibility of further data capacity optimization. Thus, we have figured how engineering advancements can dramatically change our information capacity (De Silva & Ganegoda (2016)).

In addition, this paper proposes an approach to store information into DNA. The experimental work accomplished validates the proposed approach, showing the advantages of the method that is proposed. After that, in wet lab process to create a DNA sequences. Finally, decoding the DNA sequence. The approach is very suitable for storing of large volumes of various data types. The flowchart for this approach is given in Figure 6.11. Experimental algorithm presented DNA storing to be an effective approach. Algorithm 6.2 present the encoding and decoding algorithm for storing data into DNA (Hakami et al. (2015)).

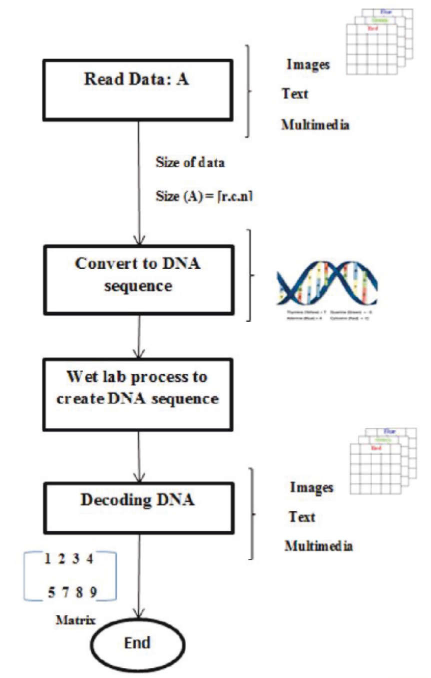


Figure 6.11: Flowchart proposed method for DNA Storage

Algorithm 6.2 Possible Approach to the DNA Computing for Big Data

A. Process

B. Encoding / Decoding algorithm

1. Encoding algorithm:

   1. Read data stream: A
   2. Check size of the data [r,c,n] = size (A) where r = rows, c = columns, n = number of matrix
   3. Calculate DNA sequences size for image
   4. Create a zero matrix of DNA sequences size
   5. While DNA sequences size = max

   - a) Convert even smallest piece of data to binary form
   - b) Insert binary DNA code of an individual data cell to DNA sequence
   - c) Continue till all of max size of DNA sequence is reached

2. Decoding algorithm:

   1. Read DNA sequence
   2. Calculate size : length, size of individual cells
   3. Convert DNA to real data decode

   - a) Convert one cell to data
   - b) Insert the converted value to template data matrix
   - c) Stop when entire DNA is converted

6.3.1 Summary

Initial research has been conducted on DNA storage, with early results pointing to its effectiveness. DNA technology for storing data is rapidly emerging as a significant and global area of research. Techniques for using DNA for storage have demonstrated significant progress, with the number of the paper published on DNA storage models and techniques increasing ten-fold each year. The methods currently being presented literally can convert even the smallest amount of information for DNA storage. This method is therefore very useful for managing and storing large amounts of and types of data.

6.4 Subjective Quality Evaluation (Survey)

Quality evaluation is one of a subjective method to evaluate the compressed image. Many approaches are proposed over time to automate the evaluation of image quality with respect to judgments in human quality. The main purpose is to present objective and subjective quality assessment methodologies and their types of classification. Distortion of digital images is a common problem that results from the imperfections of the acquisition system and data compression methodologies. Therefore, Image Quality Assessment (IQA) plays a major point in forming many visualized processing systems. The main purpose of the quality measurement of image and videos is the evaluation of humanity's comfort of perception known as the Quality of Experience (QoE). Both the individualistic nature of the observer and specific technical concerns of presentation make a difference on the quality of the image.

Thus, there are two kinds of methods for quality assessment methodologies:

1. Subjective Method
2. Objective Method

As mentioned in Chapter 2, subjective assessment methods require the human observer to evaluate the compressed images. The scores are analyzed to determine the objective indicators for image quality, when the Human Visual System (HVS) is taken to account. Objective assessment is generally used to evaluate the qualities of the distorted image with reference to the original source. These methods are used to measure the impact of technical factors on the perceptual image quality.

Human observers are the final recipients in the most image and video applications, thus a subjective evaluation is the most accurate and reliable approach. However, subjective methods have some drawbacks:

- They cannot be used in real-time applications;
- The results are influenced by physical conditions and emotional state of the observers; and
- Their results depend on viewing conditions and they are time consuming and expensive.

During the test, the observer assesses a series of images. They can be both original, or compressed images and processed images. The total number of questions is composed of a set of 24 questions. The set of questions consists of two separate sets. Questions from Number 1 to 12 are related to the general information of Data Compression, then from Question Number 13 to 24 is regarding quality evaluation based on human opinion. The focus of our experimental survey is to evaluate the human perception for compressed image quality. To better understand the Data Compression Techniques algorithm, this chapter briefly summarizes the survey questions and the participant answers. In the following section, the survey questions are divided into two parts as shown below:

1. Total Population; and
2. Quality Evaluation

6.4.1 Total Population

Focus groups revealed that in the general information regarding data compression, a large number that found of the general public selecting the right answer. Figure 6.12 present the different percentages of participant knowledgeable. It was found that 55% of participant has good information about data compression techniques. But 25% from them they are not familiar with compression techniques as shown at Table 6.12.

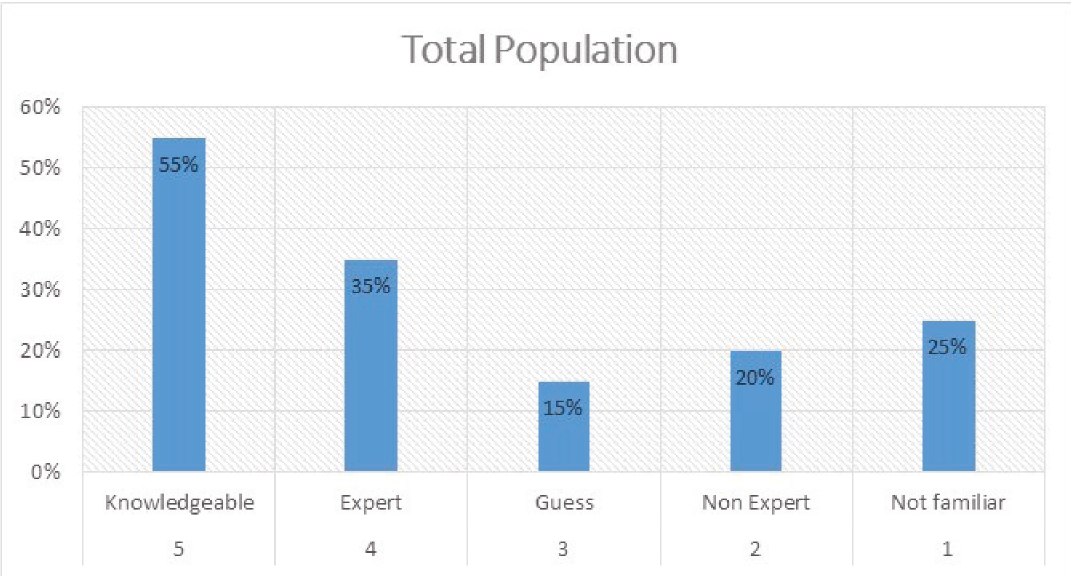


Figure 6.12: Evaluation of Participant information

Value	Information scale	Total Population
5	Knowledgeable	55%
4	Expert	35%
3	Guess	15%
2	Non Expert	20%
1	Not familiar	25%

Table 6.12: Evaluation of Participant information

This question is viewed as:

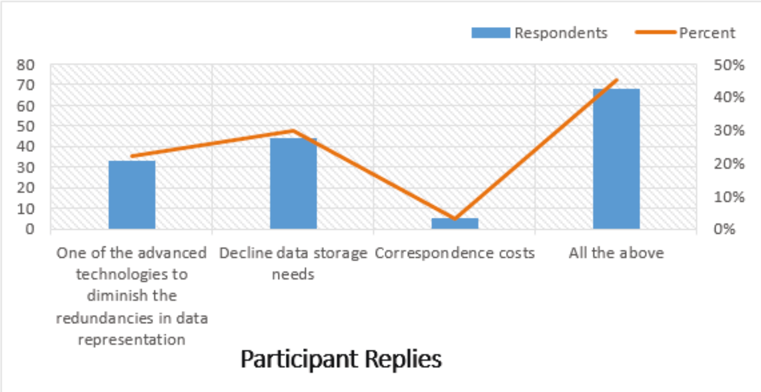
- 45% answered very well;

- 30% chose declining storage needs;
- 3% chose the cost of correspondence; and
- 22% chose the diminishing redundancies in data representation.

The questions of this survey in the following part:

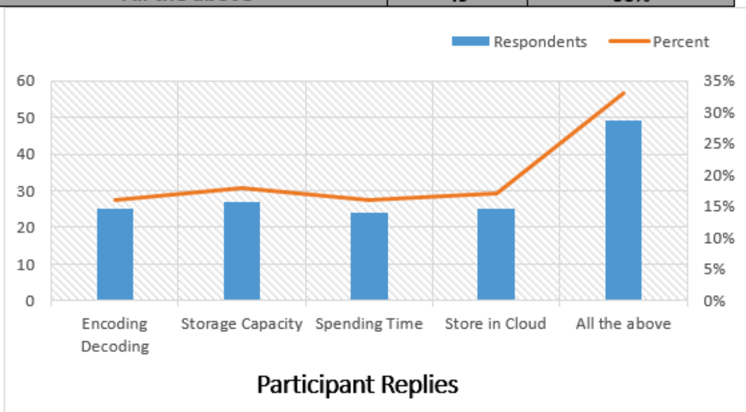
1. What is the Data Compression Technique?

Participant Replies	Respondents	Percent
One of the advanced technologies to diminish the redundancies in data representation	33	22%
Decline data storage needs	44	30%
Correspondence costs	5	3%
All the above	**68**	**45%**



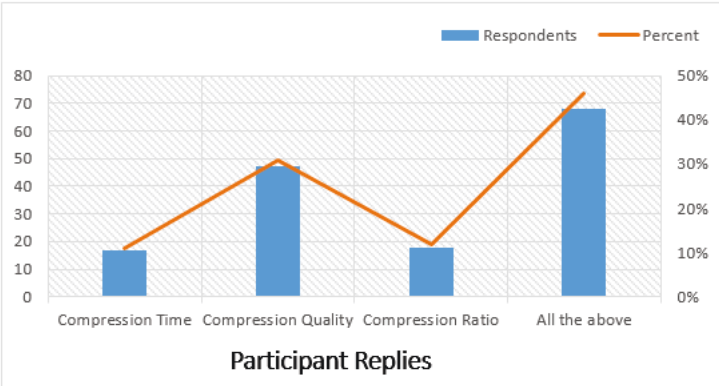
2. Do you think the compression technique is useful for effective reason: (Choose more than one if appropriate)?

Participant Replies	Respondents	Percent
Encoding Decoding	25	16%
Storage Capacity	27	18%
Spending Time	24	16%
Store in Cloud	25	17%
All the above	**49**	**33%**



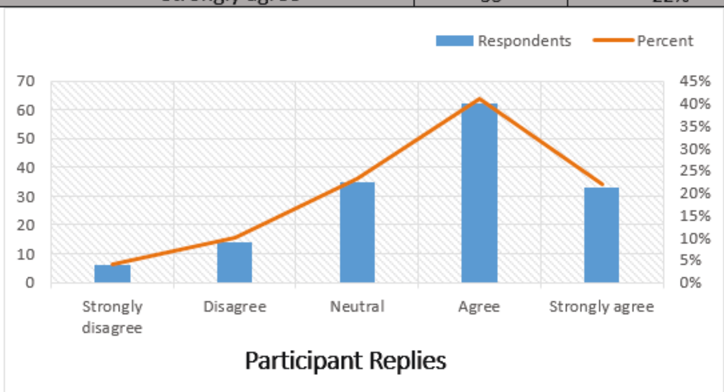
3. Is it necessary for Data Compression to be an effective technique to have a balance between the following: (Select the right answer)?

Participant Replies	Respondents	Percent
Compression Time	17	11%
Compression Quality	47	31%
Compression Ratio	18	12%
All the above	**68**	**46%**



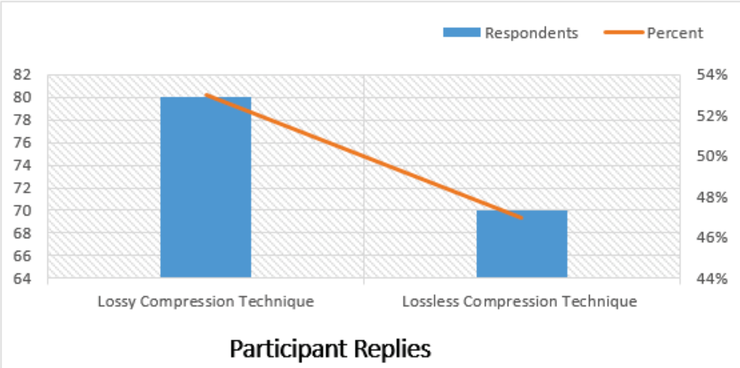
4. Do you think there is a need for an application that automatically can reduce the size of data in real time?

Participant Replies	Respondents	Percent
Strongly disagree	6	4%
Disagree	14	10%
Neutral	35	23%
Agree	**62**	**41%**
Strongly agree	33	22%



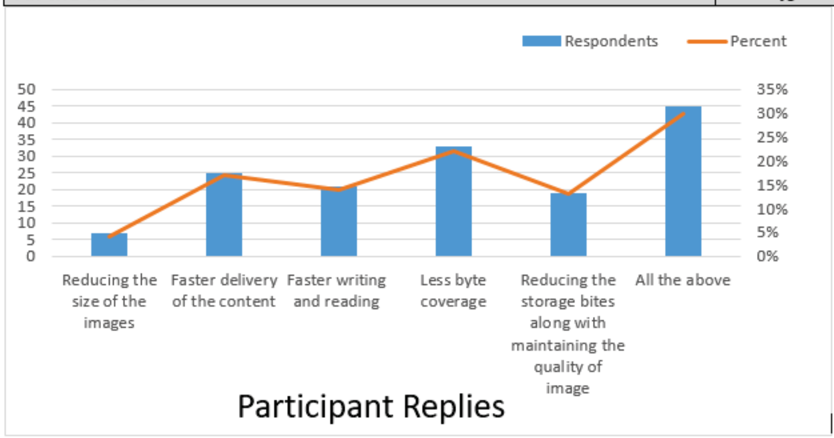
5. Which of the compression techniques stated is it irreversible to recover the original source?

Participant Replies	Respondents	Percent
Lossy Compression Technique	**80**	**53%**
Lossless Compression Technique	70	47%



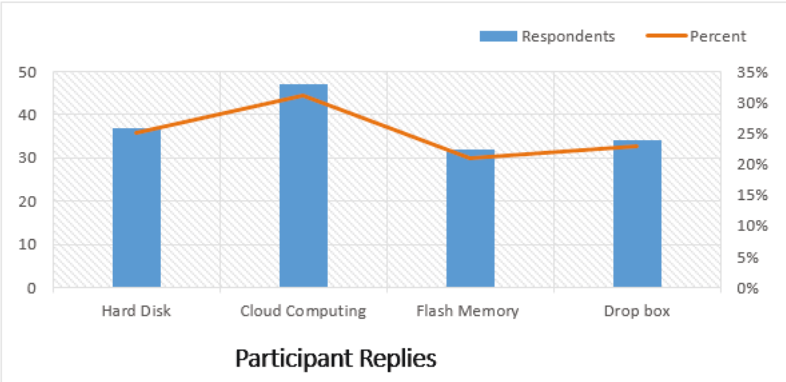
6. How should data compression techniques focus on today's needs: (Choose more than one if appropriate)

Participant Replies	Respondents	Percent
Reducing the size of the images	7	4%
Faster delivery of the content	25	17%
Faster writing and reading	21	14%
Less byte coverage	33	22%
Reducing the storage bites along with maintaining the quality of image	19	13%
All the above	**45**	**30%**



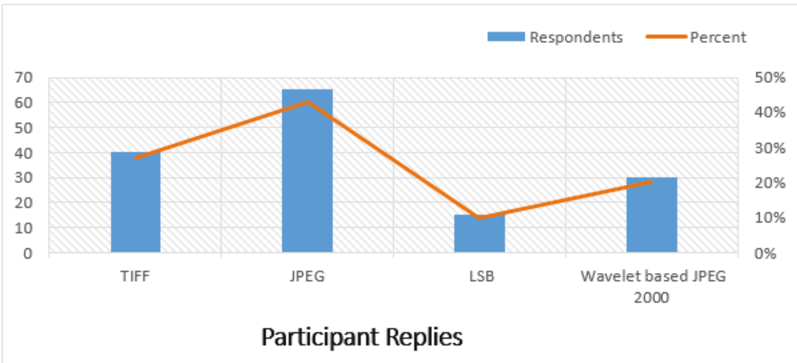
7. What is the best place to store data after compression, to save virtual space or store extensive information?

Participant Replies	Respondents	Percent
Hard Disk	37	25%
Cloud Computing	**47**	**31%**
Flash Memory	32	21%
Drop box	34	23%



8. Which one of these are compression techniques? (Choose more than one if appropriate)

Participant Replies	Respondents	Percent
TIFF	**40**	**27%**
JPEG	**65**	**43%**
LSB	15	10%
Wavelet based JPEG 2000	**30**	**20%**



9. What acceptable piece of information can be lost from the compressed image?

Participant Replies	Respondents	Percent
Progressively lose quality	24	16%
Minor loss of high resolution	55	37%
Minor loss of redundancy repeated information	**53**	**35%**
Significants loss of resolution	18	12%

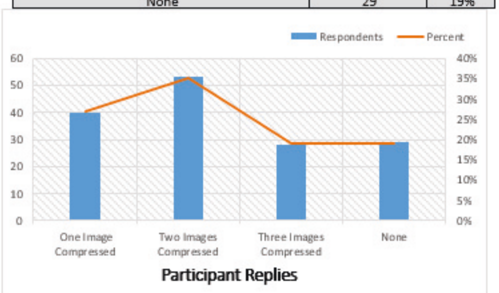
10. How many images are compressed from the previous three images?


A


B

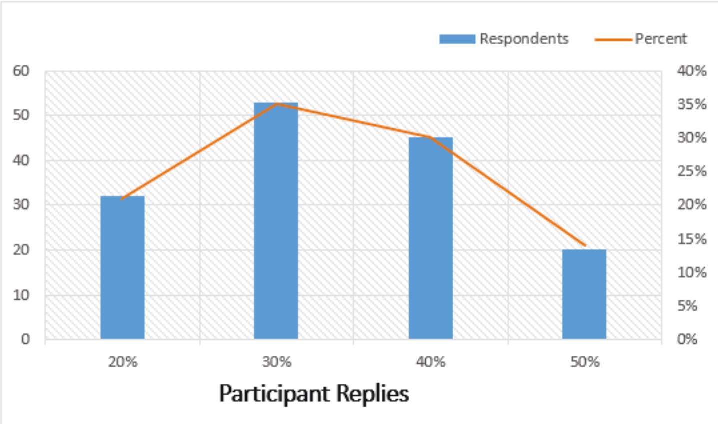

C

Participant Replies	Respondents	Percent
One Image Compressed	40	27%
Two Images Compressed	53	35%
Three Images Compressed	28	19%
None	29	19%



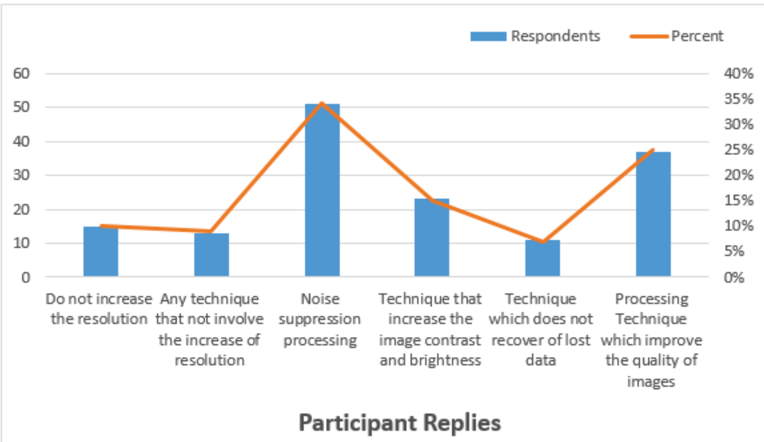
11. What is the Image Compression Ratio of the three previous images: (In Q10)?

Participant Replies	Respondents	Percent
20%	32	21%
30%	53	35%
40%	**45**	**30%**
50%	20	14%



12. How can enhancement of the image take place after compression? (Choose more than one if appropriate)

Participant Replies	Respondents	Percent
Do not increase the resolution	15	10%
Any technique that not involve the increase of resolution	13	9%
Noise suppression processing	**51**	**34%**
Technique that increase the image contrast and brightness	23	15%
Technique which does not recover of lost data	**11**	**7%**
Processing Technique which improve the quality of images	**37**	**25%**



Total Population:

The total of the right answers are 766

The number of question are 12 766 $\div$ 12 = 63.83

The percentage is 40.7 % 673 $\div$ 12 = 56.08

The percentage is 31.45 %

The total population of this survey question is 40.7 % (Highest Great)

The lowest Great of the population who skip some answers 31.45 % (Lowest Great)

6.4.2 Quality Evaluation

Data compression is the technique to lessen redundancies, thus decreasing the storage of data and thus the cost of communication. The data is elaborated as a conjunction of redundancy and information. Information is the data element that is kept safe in its particular structure to ascertain the purpose or significance of the data in a correct manner. Additionally, image compression is the most known applications of wavelet transformation.

A discrete wavelet transform (DWT) transforms a signal from the time domain to joint time-scale domain. Therefore, wavelet coefficients are of two dimensions. For the transformed signal that is compressed, the code is necessary for the coefficient values and time positioning. Thus, in an image is a signal, the point in time is conveyed as the space position. After the wavelet modifies an image, utilizing trees is accomplished due to sub-sampling performed in the modification process.

Recently, research in the field of representation of computer graphics, significant trends are focusing on the utility of wavelets, as in many other areas. Hence, wavelet transforms are developed as a vital and practical tool for the representation of signals. Wavelet transforms are used for noise reduction and compression of imagery to optimize the quality and make for efficient implementing, to accomplish better compression ratios in real time. In this chapter will evaluate human opinion regarding to compressed image quality. Figure 6.13 shows that the participant chose the compressed image has a good quality. Table 6.13 present the 19% from those participants found the compressed image has bad quality.

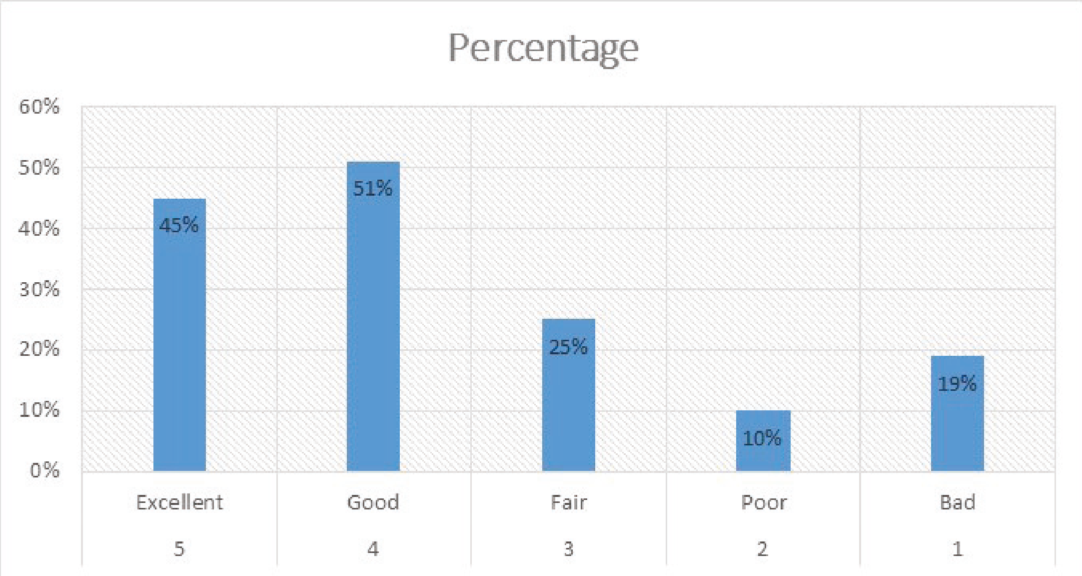


Figure 6.13: The percentage of quality evaluation

Value	Quality scale	Percentage
5	Excellent	45%
4	Good	51%
3	Fair	25%
2	Poor	10%
1	Bad	19%

Table 6.13: Percentage of quality evaluation

This question is viewed as:

- 51% chose good quality;
- 45% excellent quality;
- 19% chose a bad quality; and
- 10% chose poor quality.

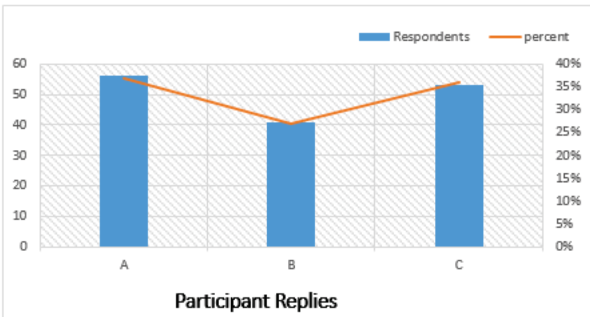
The questions of the quality part of this survey in the following part:

13. Please assess the similarity of these following three images?

Participant Replies	Respondents	percent
Identical	24	16%
Similar	83	55%
Dissimilar	43	29%

14. Which one of these images (In Q13) represents a better range of optical densities?

participant Replies	Respondents	percent
A	56	37%
B	43	27%
C	51	36%

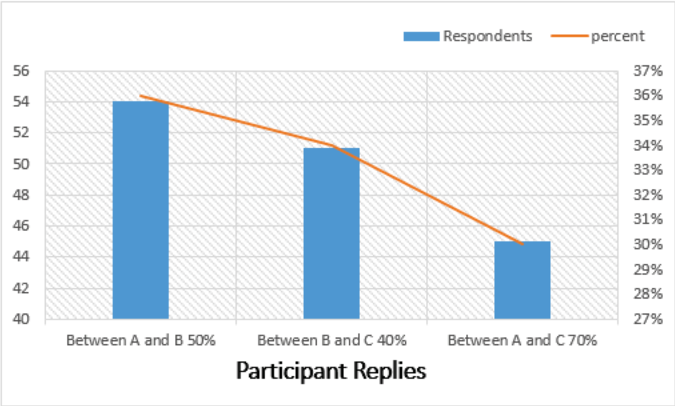


15. Can you judge the quality of each of these images (In Question 13)?

participant Replies	Respondents	percent
(A) Very Poor Quality and (B) very Good Quality	36	24%
(B) Good Quality and (C) Excellent Quality	**76**	**51%**
(C) poor Quality and (A) Very Good Quality	38	25%

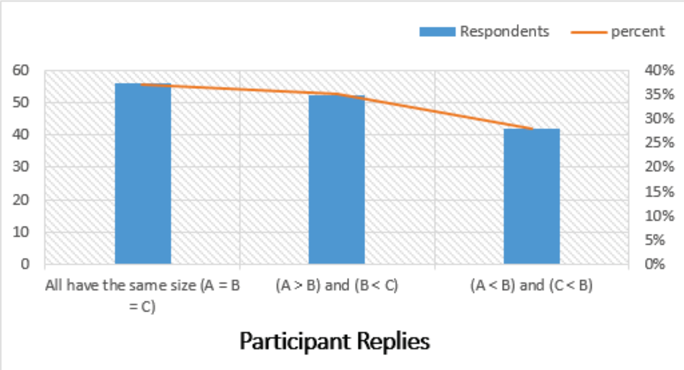
16. What is the difference between these previous three images (In Q 13) in percentage from (1-100%)?

participant Replies	Respondents	percent
Between A and B 50%	54	36%
Between B and C 40%	**51**	**34%**
Between A and C 70%	45	30%



17. Do you think the size of these above three images are:

participant Replies	Respondents	percent
All have the same size (A = B = C)	56	37%
(A > B) and (B < C)	**52**	**35%**
(A < B) and (C < B)	42	28%



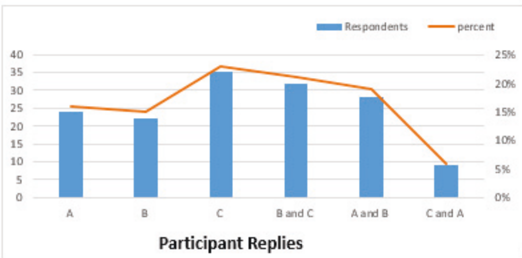
18. Which one of these images was processed using Data Compression Mechanism? (one right answer)


A

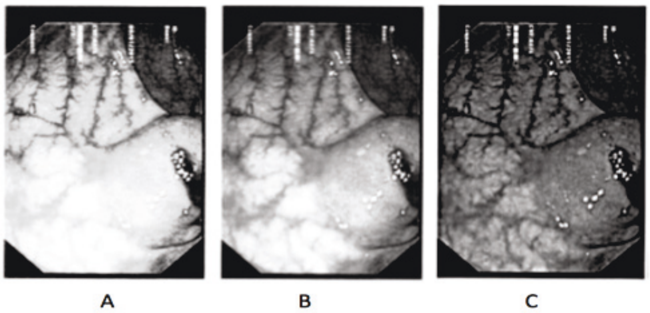

B


C

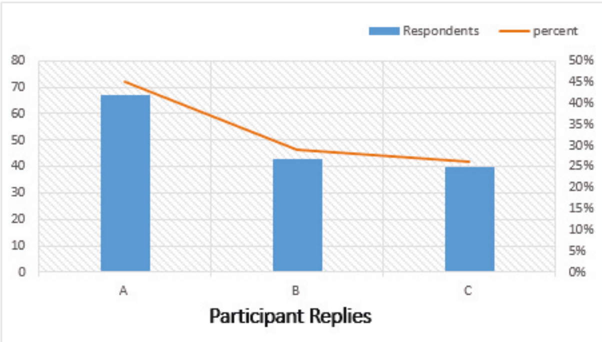
participant Replies	Respondents	percent
A	24	16%
B	22	15%
C	35	23%
B and C	32	21%
A and B	28	19%
C and A	9	6%



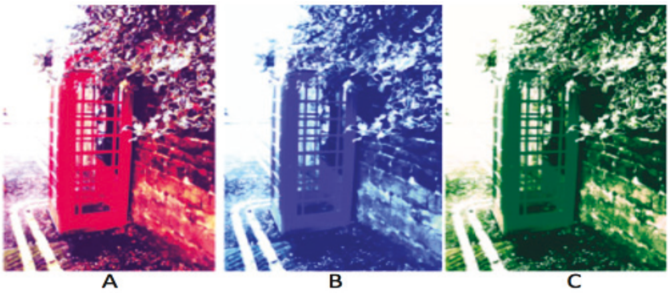
19. When assessing the quality of coloured images we consider the Luminance Component Category. which of the following images do you think is more sensitive to human eye?



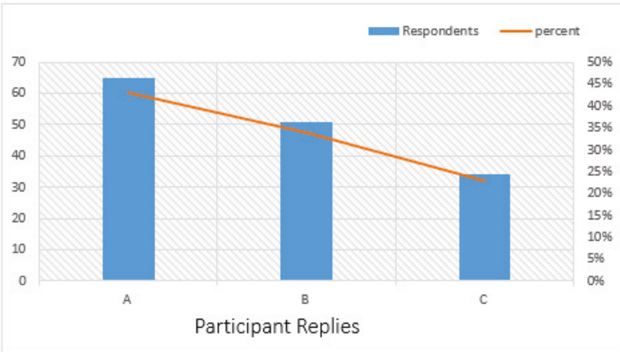
participant Replies	Respondents	percent
More Sensitive to Human Eye (A)	67	45%
Less Sensitive to Human Eye (B)	43	29%
Not Sensitive to Human Eye (C)	40	26%



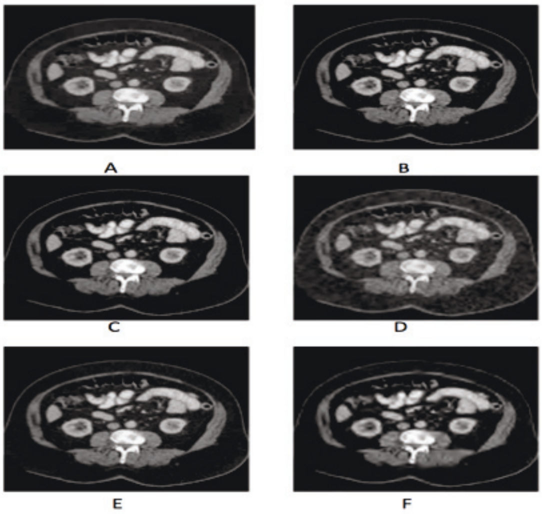
20. When assessing the quality of coloured images, we consider the Chrominance Component Category. Which of the following images do you think is more sensitive to human eye?



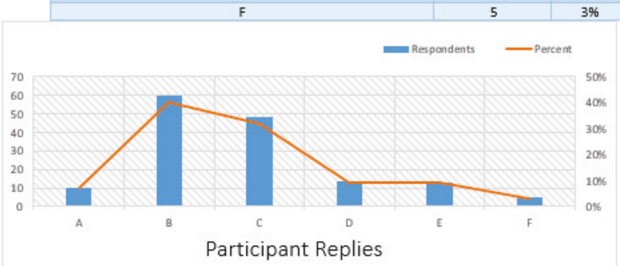
participant Replies	Respondents	percent
Not Sensitive to Human Eye (A)	65	43%
Less Sensitive to Human Eye (B)	51	34%
Sensitive to Human Eye (C)	34	23%



21. Which one of the following images has the highest quality?

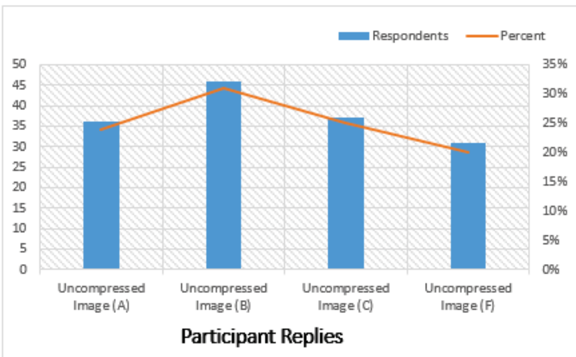


Participant Replies	Respondents	Percent
A	10	7%
B	60	**40%**
C	48	32%
D	14	9%
E	13	9%
F	5	3%



22. Which one of the previous images is uncompressed? (In Question 21)

Participant Replies	Respondents	Percent
Uncompressed Image (A)	**36**	**24%**
Uncompressed Image (B)	46	31%
Uncompressed Image (C)	37	25%
Uncompressed Image (F)	31	20%

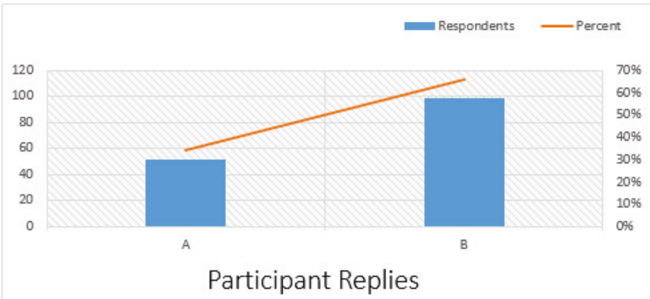


23. Which Compressed Image has the same information as the Original Image?

A

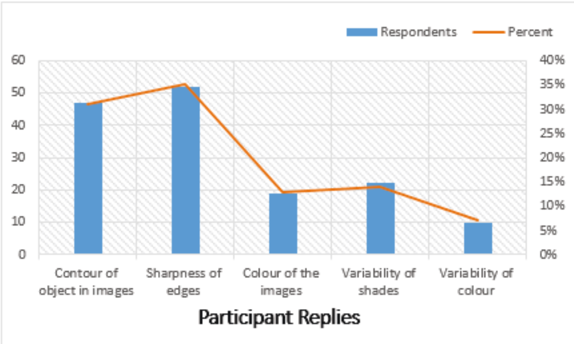
B

Participant Replies	Respondents	Percent
A	51	34%
B	99	66%



24. What type of graphical elements can be observed in the previous dark images (In Question 21)? (Choose more than one if appropriate)

Participant Replies	Respondents	Percent
Contour of object in images	47	31%
Sharpness of edges	52	35%
Colour of the images	19	13%
Variability of shades	22	14%
Variability of colour	10	7%



Total Quality Evaluation:

Total of the right answers are 681

Total of question are 12, $681 \div 12 = 56.75$

The percentage is 32.20 %

6.4.3 Summary

Conducting a subjective evaluation is an approach to evaluate the image quality in relation to human vision. There are however limitations to this evaluation technique because human vision cannot identify the differences with the compressed and original image. This chapter demonstrated that how people formulate opinions and the way in which they interact may be useful for evaluations of compressed images. However, given the differences in perception from one person to the next, there are issues around knowing which assessment or opinion to accept. As a result, a machine vision must be used to identify the differences between the compressed and the original image (see chapter 5).

6.5 Data Compression Using Steganography

Steganography refers to the process of hiding information within innocent data. Digitized imagery present as optimal places for information masking. An image that contains a hidden message is referred to as a cover image. First, for the cover image to be effective, it must render the stego image unnoticeable to human vision. The way it is embedded should not draw curiosity to the stego image to prevent hackers from trying to obtain the masked information illegally. Secondly, the method for hiding the information has to be reliable. The hidden information should not be able to be extracted without a unique extraction method and the appropriate secret key (Wazirali (2016)). Third, the hidden message should be as long as possible. Therefore, the compression technique is crucial in order to transmit the stego images in less time and to avoid crashing the hidden information as shown at Figure 6.14.

This case study objective was to conduct an examination of the compressed images following the embedding step of a hidden message (text or image) into the images. First, the original image was compressed. Following this, the 'secret' message was embedded into the compressed image. Notably, the size of the compressed image was recorded prior to embedding the hidden information as well as after the hidden information was embedded. The concealed information was then extracted from the compressed stego image. Figure 6.15 present the structure of hiding data in each colour channel.

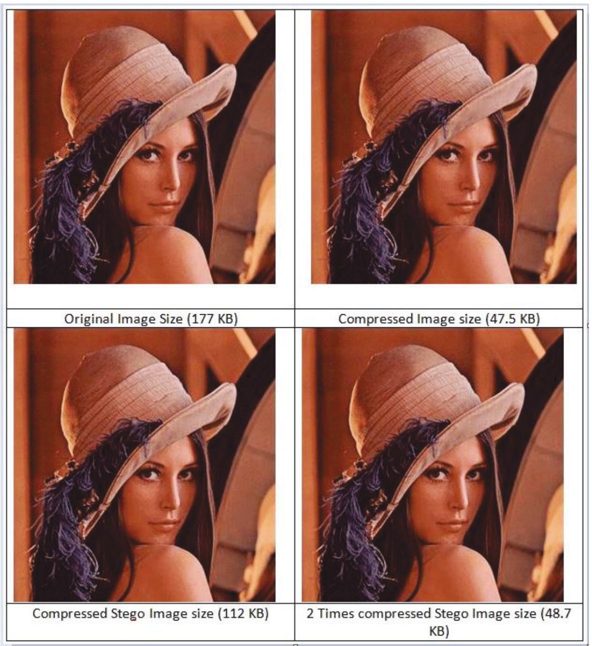


Figure 6.14: Result of compressed stego images

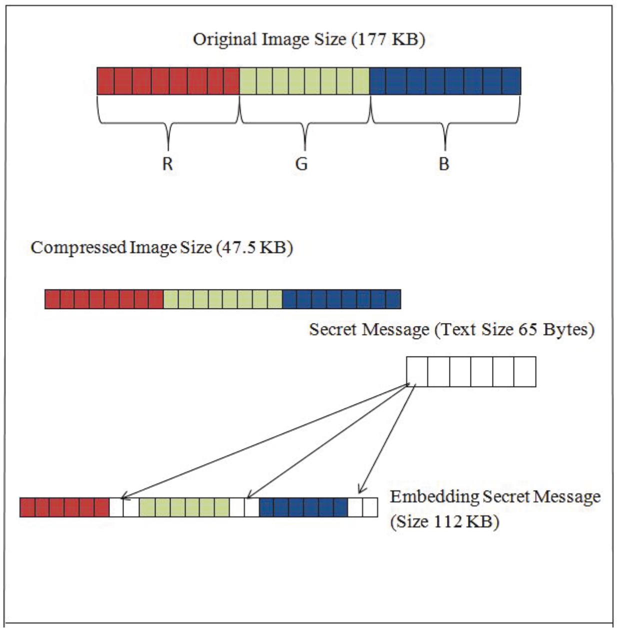


Figure 6.15: Hiding data in each colour channel

Figure 6.16 present the flowchart of compressed stego images. First, start to compress images using Discrete Wavelet Transform (DWT) then embedding any secret massage to this compressed image. After that stego compressed image appears which will be compressed again. Finally, extract the secret message and original image as present at Figure 6.14.

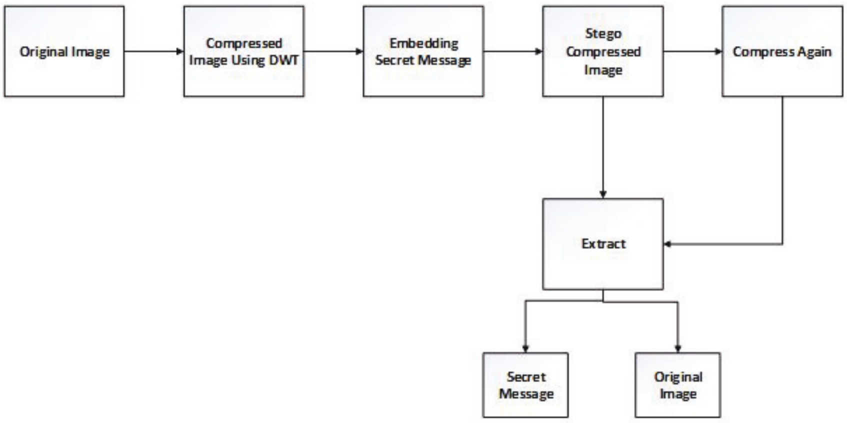


Figure 6.16: Flowchart of compressed stego images

6.5.1 Summary

This action study aims to compress the stego image that hiding the secret message using our proposed method of Lossy Compression Technique using the Human Visual System (LCT-HVS). The compression technique is one method which overcomes with the limitation for compressed stego images.

This research work shows a system dependent on critical applications of wavelet transforms to compress images. It also reviews efficient image quality metrics in terms of the Human Visual System (HVS) and its associated features. Furthermore, it also investigates how the eye of humans does not possess a greyscale error sensitivity. However, certain sensitivities are recognized by regarding image edge properties.

The main purpose of this chapter is to presents some action studies of data compression to provide an effective solution to some issues such as stitching large size images, big data storage based on DNA computing, survey to evaluate the subjective quality and data compression using steganography. A comparison of four different scenarios has been undertaken to determine the effectiveness of compression techniques.

7 Conclusion and Future Work

This chapter discusses the main conclusions drawn from the research findings and proposes future practices for the identified methods. A brief discussion of the academic contributions to this research field is also provided. The following five parts comprise this chapter:

- First part review of the proposed problem and solutions.
- The second part the research finding from experimental validations.
- The third part presents scholarly contributions.
- Fourth part summarizes limitations of the research work, and
- The fifth part gives future research directions.

7.1 Revisiting the Problem Method

7.1.1 Problem

Compression techniques to reduce the data size to have more space to store and transmission for processing was proposed and validated. The most important aspects of the data compression technique are image quality, compression ratio and processing time. These three primary factors of digital compression methods have been addressed and improved experimentally in this thesis. The research goal was to demonstrate effective solutions to address the problem of storage capacity with minimum processing time without degrading the quality of data. In order to improve image quality and enhance the compressed image using the Human Visual System (HVS), it is preferred to reduce all the redundancy with keeping the image quality.

7.1.2 Hypothesis

The hypothesis inspired by improving data compression concepts was proposed. The hypothesis suggested the usage of evaluation compression methods for improving storage capability, image quality and the perceptual quality applying compression and filtering mechanisms using wavelet techniques. Novel compression methods have been proposed in this thesis based on the research hypothesis. For lossy and lossless compression techniques, a potential solution to store, transmit and retrieve data in less time. These methods aim to manage the time of processing, quality of imagery and ratio of compression based on HVS. For improving parameters of performance for image compression in lesser time while maintaining the similar original quality.

7.2 Post Validation Research Finding

Below are the outcomes towards achieving the research aim.

7.2.1 Computational for Lossy Compression using Wavelet Transform

The research balances between the time of processing, quality of image and ratio of compression bound to the Human Visual System (HVS). In this research, a novel compression work is considered as an ideal way to store, transmit and retrieve data in less time. This proposed method Lossy Compression Techniques is built on the Human Visual System (LCT-HVS) using the 5-D multi-wavelet transform combined JPEG2000 encoding, to accomplish a compression ratio of significance, fast rate of execution and optimal image quality in a real-time manner. The experimental exercise has increased the compression performance and compared with other previous methods; it has achieved the optimum result of compression with 5-D multi-wavelet based on HVS. The optimum result from this experiment conversion achieves the peak ratio possible with the minimal distortion.

7.2.2 Computational for Lossless Compression using Wavelet Transform

The emergence of smart computing devices has significantly increased the rate at which digital images can be generated, transmitted and shared. As people's uses of small electronic devices with cameras increases, and with users being provided with increasingly efficient technologies to upload images directly to the Internet, the need for more efficient image data storage devices has also increased. Users expect to be able to store and retrieve their digital information efficiently and effectively so that it can be easily put to practical use. Approximations data can be stored much more efficiently (i.e. using less space) than original data. There will always be occasions when the original multimedia without information loss is required. In turn, data compression can be improved using a lossless method. A novel Lossless Reversible Colour Compression Technique (LRCCT-HVS) method based on the Human Visual System (HVS) has been proposed to attain optimal results.

7.2.3 Image Enhancement Compression Techniques

Image compression is increasingly necessary given the increased traffic due to multimedia information and digitized images. A novel image compression algorithms based on wavelets has improved the quality of images at high compression ratios. To lower the ratio of errors per compression and to achieve the best perceptual quality, modification to current image compression algorithms must be undertaken. The central objective of the IECT method is to improve image quality following compression via modification of the dynamic range or contrast, or both together. Increasing the contrast of the image and reducing its dynamic range while eliminating all noise can therefore enhance the image's quality significantly.

7.2.4 Validation of Compression Quality

Object detection using feature classification with compression techniques is a new approach to evaluate the compressed image quality in 2D and 3D domain. In this research, compression techniques will be applied before and after add some noise to images to represent the different environment condition for different compression levels. Based on changing environmental conditions, the measurement of performance, accuracy and quality of data can be assessed, using Support Vector Machine with compression. The highest accuracy will get with high compression, also after compression accuracy and performance marginally changes.

7.2.5 Compression Image Stitching for 3D images

The capability of data compression approaches was demonstrated by applying it in stitching image. Key features of the stitching image are has vast applications in medical imaging, computer vision, satellite imaging, video conferencing and many others also are that it is attractive and functional to storage capacity. Many tasks can be performed with the help of this application.

This case study emphasizes the development and implementation of proposed methods, within a group number of images create a large image with a high resolution that requires to reduce the size to store it in less space.

7.2.6 Big Data Storage based on DNA Computing

The significant growth in the capacity to generate data and the ever-increasing necessity for long-term data storage has increased demand for storage that has storage density and high capacity, and the ability to cope extreme conditions in the environment. The characteristics of DNA point to its potential as a data storage medium. In recent years there have been diverse encoding models developed to read and write data onto DNA, data encryption codes to address problems around error generation, and approaches to develop codons and storage styles. DNA is regarded as a possible medium for secret writing, and ultimately DNA cryptography and stenography. The uses of DNA as organic memory devices and the emergence of DNA-related big data storage and analytics has presented opportunities to exploit DNA computing to resolve computational problems.

7.3 Research Contribution

The following are the research papers that have been published to achieve the research aim and objectives:

- **"Review of HVS-based Image Compression Methods"**, published in International Journal of Computer Application (IJCA 2015)

  Presented in this paper is a review of data compression methods that apply the Human Visual System (HVS) according to set criteria. Compression characteristics, methods of compression and wavelet-based compression are included in the review. It is possible to compress digital images using processes designed to reduce image data redundancy and to save or send a particularly efficient form of data.

- **"Improve Data Compression Performance Using Wavelet Transform Based On HVS"**, published in International Conference on Image & Vision Computing New Zealand (IVCNZ 2016)

  This research paper investigation presents compression of data as a potential goal for persistence, transmission and information retrieval. Compression is particularly useful during telecommunication because it allows digital devices to facilitate data storage and transmission utilizing reduced bit size. As a result, the aim is to strike a better balance in a time of processing, data quality, and rate of compression according to HVS perception. Optimal multimedia conversion is characterized by converting at the highest rate possible with incurring the lowest amount of distortion.

- **"Reversible Colour Compression Transform for Big-Data System Using Human Visual System"**, published in 25th International Conference on Systems Engineering (ICSENG 2017)

  The core aim of compression that is lossless is to shrink bit size needed by system resources to transmit and store imagery without information loss. The Reversible Colour Compression Transform method (RCCT) generates an algorithmic approach that enables efficient compression with an acceptable level of information loss. A HVS wavelet methodology utilizing lossless compression is presented. It is an approach that effectively minimizes the time needed to compress images transformed into a $YCuCv$ colour space model utilizing an RCT. Use of the RCT via decorrelation produces superior results with substantial improvement in the performance parameters.

- **"Review of Big-Data Storage based on DNA Computing"**, published in Asia-Pacific Conference on Computer Aided System Engineering (APCASE 2015)

  This focus of this paper was on "Big-Data Storage based DNA". It elaborated both early and recent research findings, the advantages and disadvantages of DNA storage, and how the techniques will be used in future practice. This paper also proposed a simple method for storing data in DNA. The experimental work was undertaken to consider the approaches with results showing the advantage of the method being proposed.

- **Winner of Poster Presentation in Faculty Research Showcase 2016**

  In this research showcase at the University of Technology Sydney 2016, my poster was one of the winners for poster presentation regarding "Improve Data Compression Performance Using Wavelet Transform Based On HVS".

7.4 Limitation of Findings

Digital image processing is the subject of numerous publications and research studies. Some of these works have identified the time required to complete image compression as the main disadvantage. Many of the research findings published in these journals struggle are challenging to implement in real-time.

7.5 Future Work

The trade offs between performance parameters, storage capacity and image quality in data compression applications creative techniques have shown to be valuable. The future works which could have an impressive impact on the making of the proposed scheme and compressed more data without degrading the quality are discussed below:

In the 20th century, the way of life had been changed due to technology and science. The technology provides massive advantages and simplicity in our life. However, some risk has been introduced with this new technology. Development might have a high social impact, and multimedia compression is similar. Over the last decades, compression techniques established an allocation of consideration to solve space for storage and very high data rates for transmission.

Therefore, one aspect of image processing that makes it such an interesting topic of study is the amazing image compression. Indeed, when we send an image, one encounters a large volume of data. So, we should compress the image and then send it. Compression of images is an essential characteristic of image processing, otherwise the transmission of an image of large sizes over the internet would be made more difficult. Effectively, the purpose of image compression is to cut the redundancy of the image data so one can transmit or store data efficiently. Image compression is about shrinking the graphics file byte size without tarnishing the image quality to an unacceptable degree. Ethical and security impact in quite pertinent to the compressed image that corrective virus and unperceived for compressed secure. There trust and privacy issues. In this work, we provide specific permissible applications and possible technique of wavelet based on multimedia compression using HVS. Of course, the precise use of the information herein is all under the reader's responsibility.

This research is focused on 2D and 3D compression techniques using wavelet transform based on HVS. Due to the high demand for storing digital data because data is new oil today, there are lots required for future work it may lead to better data compression technology development. Some of the future works of this research are listed below:

- To overcome practical challenges, the storage in the next generation will use DNA storage capability. In the future research trying to applying our compression algorithm and designing a new biological compression storage technology.
- In the future, the research work may enhance GIF animation images using deep learning.
- The effect of applying the classification algorithm with 2D and 3D images compression techniques achieve a good result. The work continues to classify the proposed method compression algorithm for video.

8 Research Appendix

8.1 Appendix (A)

In this section present some of the lossy compression algorithms as follows:

1. **EZW Algorithm 8.1:**

Algorithm 8.2 EZW Algorithm after (Xu (1992))

1. For all images Load I = Input Images
   O = Output Images
   CR = Compression Ratio
   CT = Compression Time
   W = Discrete Wavelet Transform $(2D - DWT)$
   Achieve Optimum Result = 1
2. Apply W
3. Encoding I using Entropy Coded
4. Select Threshold T based on HVS
5. Calculate the $CR, PSNR, CT$
   $if\ |p| \prec 1$(Doesn't Achieve Optimum Result)
   repeat step 4 to 6
   else $if\ |p| \succeq 1$
   $endif$
   $end\ else$
6. Reconstruct the $2D - DWT$
7. Decoding and get O (Optimize Solution)

Algorithm 8.1 EZW Algorithm (Xu (1992))

Step 1: Initialization

$T_0 = 2^{floor(log2(max(coeffs)))}$

$K = 0$

Dominant List = All coefficients

Subortinate List = [ ]

Step 2: Significant Map

for each coefficient x in the Dominant List

    if $|x| \geq T_k$

        if $x \succ 0$

            set symbol POS

        else

            set symbol NEG

else if x is non-root part of a zerotree

            set symbol ZTD(ZeroTree Descendant)

    if x is zerotree root

            set symbol ZTR

    otherwise

            set symbol IZ

Step 3: Dominant Pass

if symbol (x) is POS or NEG (it is significant)

    put symbol (x) on the Subordinate List

    Remove x from the Dominant List

Step 4: Subordinate Pass

for each entry symbol (x) in Subordinate List

    if value $(x) \epsilon$ Bottom Half of $[T_k, 2T_k]$

    output ”0”

    else

    output ”1”

Step 5: Update

$T_{k+1} = T_k/2$

$k = k + 1$

Go to Significance Map

2. **JPEG2000 Algorithm 8.3:**

Algorithm 8.3 JPEG2000 Algorithm

---

1. Load I = Input Images
   O = Output Images
   W = Discrete Wavelet Transform $(2D - DWT)$
2. Read I pixels and perform normalization to range $[0 - 1]$
3. Divide I into non-over lapping blocks
4. Apply W
5. Execute the Quantization to I
6. Reconstruct the $2D - DWT$
7. Decoding and get the O

---

3. **SPIHT Algorithm 8.4:**

Algorithm 8.4 SPIHT Algorithm (NirmalRaj (2015))

Step 1: Initialization
Result $n = [log_2 max|C(i,j)|]$;
Let LSP= 0;
Let LIP= $(i,j) \in H$
Let LIS= $(i,j) \in H \forall D(i,j) \neq \varnothing$ *also entries* $(LIS) \in A$
Step 2: Sorting Process
for $i = 1$ to length of (LIP (i,j))
$S_n(i,j)$,
if $S_n(i,j) = 1 then$ shif $t(i,j) into\ LSP$ and out the sign of $C(i,j)$
end i
for $i = 1$ to length of (LIS (i,j))
if LIS $(i,j) \in A\ then\ result = S_n(D(i,j))$
if $S_n(D(i,j)) = 1$ then
for all $(k,1) \in O(i,j)$
result $S_n(k,1)$
if $S_n(k,1) = 1$ then add $(k,1) \rightarrow$LSP, result the sign of $C_{k,1}$
if $S_n(k,1) = 0$ then
add $(k,1)$ at end of LIP
if $L(i,j) \neq 0$ then shift (i,j) to end of LIS, and the entries $\in$ type B, else delete entry $(i,j)$from LIS
for $i = 1$ to length of (LIS (i,j))
if LIS$(i,j) \in B$ then result $= S_n(L(i,j))$
if $S_n(L(i,j)) = 1$ then
add each h_m to the end of the LIS under A, else delete $(i,j)$from LSP
Step 3: Refinement Process
for $i = all(i,j)$ in LSP$\forall i$ not appear in sorting process
n^{th} important bit of $|C_{i,j}|$
end i
Step 4: Quantization Pass
$n - -//$decrement n
go to Step $- 2$

4. **HS-SPIHT Algorithm 8.5:**

Algorithm 8.5 HS-SPIHT Algorithm (Danyali, H. and Mertins (2002))

Step 1: Initialization

Set $n = \lfloor max_{\{i,j\}} |c_{i,j}| \rfloor$ and output it

Set the LSP and LDIS as empty lists

Put the cwrdinates of all roots in H into the LIP

Put the mts in H which have descendants also into the LIS as type A entries.

Set $k = k_{max}$ where k_{max} is the maximum level of spatial scalability supported by the encoder$(1 \leq k \leq N + 1)$

Step 2. Resolution-Dependent Sorting Pass

for each entry (i, j) in the LIP do:

output $S_n(i, j)$;

if $S_n(i, j) = 1$ then move (i, j) to the LSP and

output the sign of $c_{i,j}$;

for each entry (i, j) in the LIS do:

if the entry is of type A, else:

if all coordinates in the $D(i, j)$ are located outside of the spatial resolution level k then move (i, j) to the LDIS as type A, else:

output $S_n(D(i, j))$;

if $S_n(D(i, j)) = 1$ then for each $(p, q) \epsilon O(i, j)$ do:

output $S_n(p, q)$;

if $S_n(p, 4) = 1$ then add (p, q) to the LSP and output the sign of $C_{p,q}$;

else add (p, q) to the end of the LIP;

if $L(i, j) \neq \phi$then move (i, j) to the end of the LIS as an entry of type B

else remove entry (i, j) from the LIS;

if the entry is of type B then all coordinates in the $L(i, j)$ are located outside of the spatial resolution level k then move (i, j) to the LDlS as type B; else: output $S_n(L(i, j))$;

if $S_n(L(i, j)) = 1$ then

add each (p, q) $\epsilon O(i, j)$to the end of the LIS as an entry of type A,

remove (i, j) from the LIS

Step 3. Refinement Pass

for each entry (i, j) in the LSP, except those included in the last sorting pass output the n^{th} most significant bit of $|C_{i,j}|$

Step 4. Quantization Update

decrement n by 1

if n is greater or equal to the minimum bitplane then

if $k = k_{mex}$ then go to step 2 else go to step 5

Step 5. Resolution Scale and Lists Update

if $k > 1$ then:

decrement k by 1

set the LIS. LIP and LSP as empty lists

set n with the maximum quantization level related to the first entry that was moved from the LIS to the LDlS during resolution-dependent sorting pass far resolution level $k + 1$

move back all entries in the LDIS which were moved to the LDlS during quantization level n of the sorting pass for resolution level $k + 1$, to the LIS and go to step 2

else: end of coding

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