UTS UNIVERSITY OF TECHNOLOGY SYDNEY

The Effects of Physiological Stress on Brain-Computer Interface Systems

by Howe Yuan Zhu

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Doctor of Philosophy

under the supervision of Prof. Chin-Teng Lin and Dr. Hsiang-Ting (Tim) Chen

University of Technology Sydney
Faculty of Engineering and Information Technology

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Certificate of original authorship

I, *Howe Yuan Zhu* declare that this thesis, submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the *School of Computer Science*, *Faculty of Engineering and IT* at the University of Technology Sydney, Australia.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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Howe Yuan Zhu

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Abstract

Brain-Computer Interface (BCI) devices are an emerging technology that aims to revolutionise the way humans interact with various contemporary technologies. A significant challenge to the practical use of BCI devices is the signal sensitivity to changes in a user's physical and emotional state. Factors such as muscle movement, electrical noise, workload, fatigue, and emotional state, can negatively contribute to the performance of a BCI device when being used in a real-world environment.

This work investigates how a user's physiological stress level may impact the performance of a BCI device on an Electroencephalograph(EEG) signal level. The human stress response is a universal survival mechanism that impacts both the emotional and physiological state of the body. While it is known that acute stress directly affects mental performance, its specific effects on the EEG signal behaviour and P300 response is mixed and sometimes contradictory.

We performed two novel experiments to mimic real-world scenarios that elicit a stress response. Our experiments incorporated complex visual input, auditory stimuli, and proprioceptive feedback into our experimental design to improve the future robustness of BCI system designs. The two experiments explored different types of stressors, with one being a prolonged stimuli stressor (height exposure) and the other being a dynamic stressor (unexpected drone collisions). The first experiment explores a novel elevated walking experiment that utilises a combination of physical and virtual height to induce a stress response. The second experiment investigated the potential use of unexpected drone collisions to elicit a stress response. Both experiments successfully induced a physiological stress response and produced an observable neurological change in the EEG signal.

Our results indicate that prolonged exposure (Height Exposure Experiment) to stressful stimuli creates a significant increase in frontal to parietal beta power and a lower P300 peak amplitude in some participants during a BCI task. On the other hand, a dynamic stressor (Drone Collision Exposure Experiment) tends to produce a short-term increase in frontal and central theta power, along with a negativity response during the stimuli. Collectively these findings provide insights into how different forms of physiological stress affects BCI devices on an EEG signal level and furthers the development towards a practical, real-world BCI device.

DEDICATION

To the Almighty God that create such amazing indecipherable mysteries for us to explore and grasp in our days. To my wife Louise and family who supported, guided, and shaped who I am today. . .

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List of Publications

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2. **H.Y. Zhu**, H.-T. Chen, and C.-T. Lin, *The Effects of Height-Induced Stress on Human Brain Dynamics during a P300 Task*, (***Drafted***).

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2. T. T. L. NGUYEN, **H.Y. ZHU**, H. -T CHEN, *Remote Visual Line-of-Sight: A Remote Platform for theVisualisation and Control of an Indoor Drone using Virtual Reality.*, 27th ACM Symposium on Virtual Reality Software and Technology Poster (**VRST**), Osaka, Japan, 8 - 10 Dec., 2021. **(Accepted)**

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