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A physiological signal-based method for early mental-stress detection

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ABSTRACT

The early detection of mental stress is critical for efficient clinical treatment. As compared with traditional approaches, the automatic methods presented in literature have shown significance and effectiveness in terms of diagnosis speed. Unfortunately, the majority of them mainly focus on accuracy rather than predictions for treatment efficacy. This may result in the development of methods that are less robust and accurate, which is unsuitable for clinical purposes. In this study, we propose a comprehensive framework for the early detection of mental stress by analysing variations in both electroencephalogram (EEG) and electrocardiogram (ECG) signals from 22 male subjects (mean age: 22.54 ± 1.53 years). The significant contribution of this paper is that the presented framework is capable of performing predictions for treatment efficacy, which is achieved by defining four stress levels and creating models for the individual level. The experimental results indicate that the framework has realised an accuracy, a sensitivity, and a specificity of 79.54%, 81%, and 78%, respectively. Moreover, the results indicate significant neurophysiological differences between the stress and control (stress-free) conditions at the individual level.

1. Introduction

Mental stress may be defined as the effect of an excessive workload under a time constraint to meet the expectation [1–4]. It causes a person to become incapable of coping with a perceived threat to their physical, emotional, or psychological well-being. Stress and its related health conditions can pose a serious threat to the quality of life, and dysfunction in daily life can interfere with the social life and physical health of an individual. Stress is associated with a range of behavioural [5,6], cognitive [7], neurovascular [8], cardiovascular [9], and molecular effects [10].

The cognitive activation theory of stress (CATS) describes the association of the brain with mental stress [11]. There exists evidence of stress-related cognitive interference that leads to memory weakness [12] and the destruction of mental and physiological well-being [13]. Stress has been reported to be associated with the shrinkage of the hippocampus and prefrontal cortex [14] as well as the impairment of prefrontal networks [15]. In chronicity, stress can turn into stress-related diseases with serious impacts, including burnout, depression, and post-traumatic stress disorder [13,16].

Mental stress has been practically assessed through questionnaires such as the Perceived Stress Scale (PSS) [17], the Life Events and Coping Inventory (LECI) [18], and the Stress Response Inventory (SRI) [19]. Unfortunately, they only inspect stress symptoms after a person has become stressed and only provide subjective solutions, which delay treatment. Subjective feelings cannot indicate the cognitive impairment. Moreover, they can be incorrectly evaluated owing to a person's unwillingness to admit that they are under stress. Therefore, to guarantee an accurate diagnosis, there is a requirement for objective assessment methods in order to quantify stress using neuroimaging modalities.

Electroencephalography (EEG) is a neuroimaging modality that is widely used to measure brain activity as it is non-invasive and comparatively low cost. Clinically, EEG has been used as a standard neuroimaging modality to observe the neural dynamics of the human brain. EEG signals reveal how information is processed in the brain. Recently, the EEG recording ability has been improved owing to technological advances.

In laboratory settings of stress assessment using EEG, stress is first induced on known scales that lead to its assessment in stress versus control. Previous studies on the detection of mental stress can be mainly categorised into three categories: 1) the studies were related to concentration in a simulation environment, e.g. stress evaluation of drivers during driving [20,21]; 2) they included tasks of varying difficulty such that the mental or physical states could be

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identified and differentiated between the tasks [22,23]; and 3) they involved the assessment of stress using emotional methods [24–26] such that different emotional states could be identified. Recently, the Montreal Imaging Stress Task (MIST) has been validated as a paradigm for inducing stress in a functional magnetic resonance imaging environment [27]. Its suitability in an EEG environment is still unexplored. EEG has spatially and temporally abundant recording that makes it difficult to conclude the diagnosis only through a visual inspection of the recording. Therefore, optimum analysis techniques are essential for the detection of mental stress using EEG signals. Analyses exist for extracting the EEG features that represent the entire dataset. These techniques include time domain analyses such as the use of the Hjorth parameter [28], entropy [29], frequency domain analysis, which includes the analysis of power in different frequency bands [30], and time–frequency analysis, which includes the use of the wavelet transform [31]. The obtained features are then fed to classifiers for classification or diagnosis. Classifiers such as the linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA), support vector machine (SVM), regression analysis, multi-layer perceptron, and artificial neural networks [32] are commonly used [33].

Conventional EEG features lack the ability to represent the connectivity of various brain regions and to indicate how the regions communicate with each other under stress conditions. Recently, the quantitative EEG (qEEG) features have broadened the scope of application of EEG owing to their implication in some contemporary treatment techniques such as neurofeedback [34]. The qEEG features such as coherence [35], amplitude asymmetry [36], phase lag, relative power, and power ratios [37] are significantly useful in describing functional brain connectivity under mental stress conditions. Technically, only the features that can contribute to the assessment of stress are of significance with stress. Furthermore, some of the features are redundant as they can only increase the computational cost with minimal contribution to the result. Significance and redundancy can be tackled through feature selection and dimensionality reduction. The former provides the significance of a feature as compared with class variables, whereas in the latter, features are compared among each other in the feature space. If two features are similar, the one with the least contribution is discarded.

We aim to develop a methodology for detecting mental stress in the early stages by quantifying the stress into four levels. The subjects recruited should have a minimum prior stress such that we may inspect how stress affects a normal person. In order to induce a stress response, MIST is applied. qEEG-based features including relative power, power ratios, amplitude asymmetry, coherence, and phase lag are extracted from the EEG signals recorded during the experiment. The extracted features are optimised through normalisation, feature selection using the paired *t*-test, and dimensionality reduction with principal component analysis (PCA). A classifier model based on SVM using the radial basis function (RBF) kernel and sigmoid kernel is then applied to the optimised feature set.

2. Methodology

2.1. Experiment design and data acquisition

2.1.1. Experiment design

An experimental paradigm based on MIST [27] is designed, as shown in Fig. 1, for inducing and evaluating mild psychological stress in terms of physiology and brain activation by using EEG. It is a computer-based tool that induces mild psychological stress in terms of physiology and brain activation [38,39] and is commonly used to explicitly evaluate responses in stress and control conditions. In this case, both the stress and control conditions were simulated in two separate sessions with at least a seven-day gap to reduce the learning effect on the performance and to minimise hypothalamic pituitary adrenal axis activation [40]. Each session consisted of four sequential blocks: habituation, rest, mental arithmetic task, and recovery.

In the habituation training block, signals were not recorded. This block was used to make the subject accustomed to the experimental environment. It was started with on-arrival rest and briefing of the experiment for 5 min. Subsequently, the subject was presented with sample questions of an arithmetic task. The answer to every question was a single-digit number (0–9). The subject was required to press the right key while looking at the screen to minimise eye movement.

The rest block was observed as the baseline for activations under each of the stress and control conditions. Physiological signals were recorded in the rest condition for 5 min. The subject was required to sit in a relaxed position with their hands lying on their thighs with open palms, their upper teeth separated from the lower teeth with the tongue floating inside the mouth, their feet touching the floor, and their legs not crossing each other. The subject was required to focus on a circle appearing on a computer screen in front of them. All these measures were taken to reduce the possibility of movement of the subject such that unwanted artefacts may be minimised.

The mental arithmetic task block was the core of the experiment design. The task was conducted differently in separate sessions under both stress and control conditions. Both conditions had similar arithmetic tasks. An arithmetic task included up to four numbers (maximum 99) using four operands (addition (+), subtraction (-), multiplication ($\times$), and division (/)), e.g. $2 + (5 \times 25) / 5$. It contains four levels (L1–L4). Level 1 involved the addition or subtraction between only two numbers, level 2 addition and subtraction between three numbers, level 3 multiplication along with addition and subtraction between four numbers, and level 4 any four operations between four numbers. The answer to every task was a one-digit number, and the subject was required to respond by pressing the correct key. There were four levels under each condition, each of which lasted 5 min. Under the stress condition, the subject performed mental arithmetic tasks on a computer with a time limit, i.e. the time for each task was limited such that the subject could not exceed an accuracy of 50%. Along with time limit in each task, an extra text message ("delaying response text" and "speed up text") were displayed on the screen with stimuli aiming to distract the subject from the actual task and to induce additional stress in him/her. After each task, a feedback displaying the response time and correct/incorrect/no response based on the attempt appeared on the screen. Moreover, after certain trials, a stressful feedback in terms of orders appeared on the screen. This feedback reveals the external pressures that a worker faces in a work environment parallel to the job. The procedure for the control condition was the same as the one for the stress condition but without a time restriction and stress-inducing feedbacks. The aim of the control condition was to compare any cerebral activation caused by the mental arithmetic aspects of the task. This would aid in declaring the activation caused by mental stress in stress conditions with greater accuracy. The feedback display ("correct" or "incorrect") remained after each task in the control condition. Finally, the recovery time was computed to determine the changes in terms of signals when the subject is again under the relaxed condition. In this case, details for both the ECG and EEG are recorded for 5 min.

2.1.2. Subject selection and data acquisition

The experiment is accredited by the ethics commission in Hospital Universiti Sains Malaysia, Malaysia. Twenty-two healthy male subjects (mean age of 22.54 ± 1.53 years) were selected from Universiti Teknologi Petronas, Malaysia. They were selected based on