AN ENHANCED STRESS INDICES IN SIGNAL PROCESSING BASED ON ADVANCED MATTHEW CORRELATION COEFFICIENT (MCCA) AND MULTIMODAL FUNCTION USING EEG SIGNAL

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I hereby declare that I have checked this thesis and in my opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Doctor of Philosophy.

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I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

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ABSTRAK

Tekanan boleh ditakrifkan sebagai perasaan ketegangan dan tekanan di sekeliling yang berpunca daripada pelbagai faktor persekitaran, psikologi, dan sosial yang melibatkan manusia dalam tindak balas fizikal dalaman atau luaran dan keadaan emosi. Secara amnya, keadaan tekanan dikategorikan dari segi tahap tekanan yang kebiasaannya menggunakan tiga tahap tekanan iaitu tekanan tahap rendah, tekanan tahap sederhana dan tekanan tahap tinggi. Walaubagaimanapun, tiga tahap tekanan ini menjadi satu limitasi untuk kaedah yang sedia ada. Oleh itu, kajian ini bertujuan untuk mengatasi limitasi ini dan mengenal pasti kaedah yang lebih baik untuk mengektraksi ciri EEG dan mengkategorikan keadaan tekanan secara mendalam. Cadangan utama kajian ini terletak kepada pembaharuan kategori tahap tekanan dari tiga tahap kepada enam tahap menggunakan konsep terbaharu skala pecahan berdasarkan skala kuantiti yang dipengaruhi oleh MCCA dan prestasi persamaan multimodal. Konsep sisihan piawai (STD) yang membahagikan skala kuantiti, juga membawa kepada pembaharuan proses dan mengenal pasti tahap tekanan. Kelemahan prestasi Matthew Correlation Coefficient (MCC) boleh dilihat daripada prestasi ketepatan . Malah, multimodal jarang dibiacarakan dari segi parameter. Justeru, MCCA dan persamaan multimodal ini telah menjadi satu platform untuk penambahbaikan prestasi ketepatan yang akan menjadi sebahagian sumbangan kajian ini. Kajian ini memperkenalkan konsep baharu iaitu Advanced Matthew Correlation Coefficient (MCCA) dan menggunakan konsep six sigma untuk memberikan prestasi ketepatan yang tinggi dan peningkatan kategori tahap tekanan. Kajian ini fokus untuk perkembangan tiga tahap kepada enam tahap mengunnakan skala pecahan tahap tekanan yang dipengaruhi oleh Advanced Matthew Correlation Coefficient (MCCA) dan prestasi persamaan multimodal. Selain daripada itu kajian ini menggunakan kaedah pra-pemprosesan isyarat dan mengasingkan isyarat EEG kepada jalur frekuensi seperti Delta, Theta, Alpha, dan Beta. Pengekstrakan ciri EEG secara langsung meghasilkan dua puluh satu ciri termasuk fungsi statistik dan bukan statistik. Pengekstrakan ciri-ciri ini digunakan dalam fungsi MCCA dan Multimodal. Kajian ini menggunakan Support Vector Machine (SVM), Random Forest (RF) dan k- Nearest Neighbor (k-NN) untuk proses pengesahan dalam peningkatan tahap tekanan. Daripada penemuan itu, RF memperoleh ketepatan purata prestasi terbaik 85% ±10% dalam teknik 10-Fold dan K-Fold berbanding dengan SVM dan k-NN. Kesimpulannya, kajian ini telah memperharui kaedah untuk kategori tahap tekanan dan dan pegekstrakan ciri EEG. Rangka kerja MCCA yang ditubuhkan dan enam konsep sigma berjaya menyumbangkan prestasi ketepatan yang lebih tinggi, berbanding tiga kategori tahap tekanan yang sedia ada. Keputusan juga menunjukkan prestasi Random Forest lebih bagus berbanding SVM dan k-NN. Justeru, kajian ini akan memberi implikasi kepada pelbagai penggunaan dan bidang, kerana menggunakan persamaan yang lebih efektif yang membawa kepada perkembangan kategori tahap tekanan dengan hasil prestasi ketepatan yang dicapai lebih daripada 95%.

ABSTRACT

Stress is a response to various environmental, psychological, and social factors, resulting in strain and pressure on individuals. Categorizing stress levels is a common practise, often using low, medium, and high stress categories. However, the limitation of only three stress levels is a significant drawback of the existing approach. This study aims to address this limitation and proposes an improved method for EEG feature extraction and stress level categorization. The main contribution of this work lies in the enhanced stress level categorization, which expands from three to six levels using the newly established fractional scale based on the quantities' scale influenced by MCCA and multimodal equation performance. The concept of standard deviation (STD) helps in categorizing stress levels by dividing the scale of quantities, leading to an improvement in the process. The lack of performance in the Matthew Correlation Coefficient (MCC) equation is observed in relation to accuracy values. Also, multimodal is rarely discussed in terms of parameters. Therefore, the MCCA and multimodal function provide the advantage of significantly enhancing accuracy as a part of the study's contribution. This study introduces the concept of an Advanced Matthew Correlation Coefficient (MCCA) and applies the six-sigma framework to enhance accuracy in stress level categorization. The research focuses on expanding the stress levels from three to six, utilizing a new scale of fractional stress levels influenced by MCCA and multimodal equation performance. Furthermore, the study applies signal pre-processing techniques to filter and segregate the EEG signal into Delta, Theta, Alpha, and Beta frequency bands. Subsequently, feature extraction is conducted, resulting in twenty-one statistical and non-statistical features. These features are employed in both the MCCA and multimodal function analysis. The study employs the Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Neighbour (k-NN) classifiers for stress level validation. After conducting experiments and performance evaluations, RF demonstrates the highest average accuracy of 85%–10% in 10-Fold and K-Fold techniques, outperforming SVM and k-NN. In conclusion, this study presents an improved approach to stress level categorization and EEG feature extraction. The proposed Advanced Matthew Correlation Coefficient (MCCA) and six-sigma framework contribute to achieving higher accuracy, surpassing the limitations of the existing three-level categorization. The results indicate the superiority of the Random Forest classifier over SVM and k-NN. This research has implications for various applications and fields, providing a more effective equation to accurately categorize stress levels with a potential accuracy exceeding 95%.

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