Classification of EEG based-Mental Fatigue using Principal Component Analysis and Bayesian Neural Network

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Abstract— **This paper presents an electroencephalography (EEG) based- classification of between pre- and post- mental load tasks for mental fatigue detection from 65 healthy participants. During the data collection, eye closed and eye open tasks were collected before and after conducting the mental load tasks. For the computational intelligence, the system uses the combination of principal component analysis (PCA) as the dimension reduction method of the original 26 channels of EEG data, power spectral density (PSD) as feature extractor and Bayesian neural network (BNN) as classifier. After applying the PCA, the dimension of the data is reduced from 26 EEG channels in 6 principal components (PCs) with above 90% of information retained. Based on this reduced dimension of 6 PCs of data, during eyes open, the classification pre-task (alert) vs. post-task (fatigue) using Bayesian neural network resulted in sensitivity of 76.8 %, specificity of 75.1% and accuracy of 76%. Also based on data from the 6 PCs, during eye closed, the classification between pre- and post- task resulted in a sensitivity of 76.1%, specificity of 74.5% and accuracy of 75.3%. Further, the classification results of using only 6 PCs data are comparable to the result using the original 26 EEG channels. This finding will help in reducing the computational complexity of data analysis based on 26 channels of EEG for mental fatigue detection.**

I. Introduction

Mental fatigue is associated with symptoms of mental tiredness, cognitive dysfunction and loss of motivation following engagement in a demanding task for a prolonged duration of time. As a result, mental fatigue impairs task performance, including skill deterioration and elevated anxiety. Mental fatigue is believe to be highly associated with accidents in the workplace [1]. Mental fatigue may also impact a person's performance when using hands-free brain computer interfaces, requiring attention and concentration to perform mental tasks for significant period of time. Therefore, a tool for automatic mental fatigue detection is needed that alerts the user of their fatigue status, and help to restore their attention and mental capacity [1, 2, 3].

Currently state, mental fatigue can be assessed by using either psychological or physiological measurement techniques. Psychological fatigue measurement methods are based on individual responses to psychometric questionnaires. This method will be cumbersome as practical countermeasure of mental fatigue, given subjective responses to the questionnaire most likely is done offline. Moreover psychological self-report of their fatigue result in a biased outcomes (e.g. purposely underestimating fatigue for liability reason). Physiological strategies of fatigue measurement include using video recordings for facial analysis, electrocardiography (ECG) for detecting heart rate activity or variability [4], electrooculography (EOG) and eye tracking devices for detecting eye activity and electroencephalography (EEG) for detecting brain activity [5]. This paper explores further the use of EEG as promising method for mental fatigue measurement, as EEG classification system can be used in online system and it measures neurophysiological rhythmic activity directly [3].

The basic block diagram of the classification EEG-based mental fatigue study comprises of the EEG data collection, signal pre-processing, feature extraction, and classification [6]. Normally in the EEG dataset comprises data derived from a certain number of EEG channels, reflecting the dimension of the dataset. The more EEG channels used increases the dataset dimension and this directly increases the computational complexity of performing further signal processing methods. This paper combines the use of the principal component analysis (PCA) for data dimensional reduction, power spectral density (PSD) as the feature extraction method and Bayesian neural networks (BNN) as the classification algorithm for classifying between pre-task (alert) and post-task (fatigue). PCA is used here to help transforming from a high dimensional EEG dataset to a low dimensional orthogonal feature set while still retaining the maximum information of the original high dimension dataset.

II. Methodology

A. Components of EEG-based Mental Fatigue Analysis

The main components used in this study are shown in Fig.1. The process began with an experiment that induced mental fatigue in healthy participants, with the recorded data using EEG and continued by applying dimension reduction method using PCA method on the original dataset from 26 EEG channels. After PCA, low dimension orthogonal

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features were obtained. This is continued with a segmentation process and feature extraction using PSD, which is then classified using BNN.

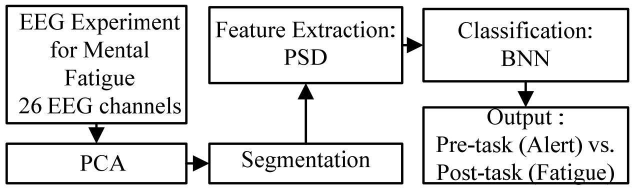

Figure 1. Block diagram of EEG-based mental fatigue study

B. *Experiment of Data Collection for Mental Fatigue*

The mental fatigue experiment EEG dataset was obtained from a previous experimental study reported elsewhere [7] involving 65 healthy participants aged between 17 to 69 years. Participants were assessed over a period 2-3 hours as they performed cognitively challenging mental tasks controlled laboratory condition. This research was approved by the Institutional Human Research Ethics Committee and conducted according to ethical research principles.

The protocol of the experiment is divided into three sections: pre-task EEG measurement, mental work load task for inducing mental fatigue and post-task EEG measurement. First, participants were asked to open or close their eyes with duration of 30 seconds, and this data was used as pre-task (alert) dataset. Second, participants were asked to conduct a series of mental workload task with the duration of around 90 minutes designed to result in fatigue. The mental work load tasks included an auditory habituation task, an auditory oddball task, Stroop/go-no-go task, an eye tracking task, visual working memory tasks, an executive maze task and a pre-pulse inhibition task. Third, after completing the series of mental workload tasks, the EEG of the participants were again assessed when participants opened and closed their eyes for duration of 30 seconds each, and this data was used for post-task (fatigue) dataset. Mental fatigue was determined using a validated self-report questionnaire called IOWA Fatigue Scale, as well as EOG assessing eye blink measurement. The IOWA Fatigue Scale has been shown to be reliable tool for mental fatigue assessment [5]. Eye blink rates have also been shown to be a reliable assessment of increased when fatigue [5].

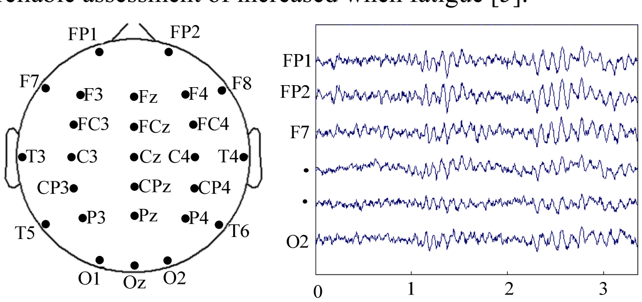

Figure 2. The 26-EEG channels location and its raw data from this study

For EEG measurement, the study used a Quick cap – Compumedics Neuroscan system with 26 EEG channels placed over the scalp using standardized position included [7]: FP1, FP2, F7, F3, Fz, F4, F8, FC3, FCz, FC4, T3, C3, Cz, C4, T4, CP3, CPz, CP4, T5, P3, Pz, P4, T6, O1, Oz, and O2 (F=frontal, C=central, P=parietal, T=temporal, O=occipital). The average EEG at mastoid locations A1 and A2 were used for reference. The impedance recording was kept below 5kOhm and the sampling rate was 500Hz.

C. *Principal Component Analysis (PCA) for dimensional reduction*

Here the PCA was used to reduce the high dimension of the 26 EEG channel data into a lower dimension involving an orthogonally linear transformation that convert the EEG data into new coordinate system or principal component (PCs) with the first principal component (PC) containing the greatest variance, the second PCs as the second greatest variance and so on [8, 9]. Given a set of N centered of raw EEG dataset,

$$x_k, k = 1,\dots, M, x_k \in R^m, \text{and } \sum_{k=1}^{M} x_k = 0 \tag{1}$$

where M denotes the number of EEG samples or participants, N denotes the number of input values or the number of EEG channels. The calculation of the covariance matrix (C) of PCA as follows:

$$C = \frac{1}{M}\sum_{j=1}^{M} x_j x_j^T \tag{2}$$

where $x_j x_j^T$ is a vector of $N \times N$ matrix. PCA needs to solve the eigenvector as follows:

$$\lambda u = Cu \tag{3}$$

where u denotes the eigenvectors of C and λ denotes the eigenvalues. Based on the eigenvector (u), the principal components of s_t as the orthogonal transformation of x_t can be calculated as follows:

$$s_t = u^T x_t \tag{4}$$

The principal components contain the maximum variance in the data defined by set of mutually orthogonal eigenvectors. These eigenvectors are ranked in a descending order of eigenvalues. By choosing only first few eigenvectors, PCA performs a dimension reduction from the high dimensional raw EEG dataset of EEG channels into low dimensional features containing only a few principal components.

D. *Features Extraction and Classification*

Before feature extraction, data from the process of PCA were segmented by applying a moving window of 2s with overlapped 1.5 seconds. The power spectral density (PSD) [6, 10] was applied to 2s of PCs segments to convert the data segment into frequency domains. EEG bands used for the features include delta band from 0.5Hz to 3Hz, theta band from 3.5Hz to 7.5Hz, alpha band from 8Hz to 13Hz and beta band from 13.5Hz to 30Hz. The total PSD value of each EEG band was used with the calculation based on the trapezoidal rule of numerical integration.

For the classification algorithm, Bayesian neural networks (BNN) was used [6, 11, 12]. BNN is a non-linear classification method able to handle the general classification problem of overfitting. The probability distribution of the network parameters is considered in Bayesian learning to provide the best generalization of the network. The BNN structure uses a 3-layers (input, hidden and output layers) feed-forward structure as follows:

$$z_k(x,w) = f\left(b_k + \sum_{j=1}^{l} w_{kj} f\left(b_j + \sum_{i=1}^{m} w_{ji} x_i\right)\right) \quad (5)$$

where *f(.)* is based on the hyperbolic tangent of transfer functions, m is the input nodes number, l is the hidden nodes number, p is the number of outputs, w_{ji} is the weight to the hidden unit y_j from input unit x_i, w_{kj} denotes the weights to output (z_k) from hidden unit (y_j), b_j and b_k are the biases. In the BNN framework, the weights of the network are based on minimizing the cost function as follows:

$$F(w) = \beta E_D(w) + \alpha E_W(w) \quad (6)$$

where $F(w)$ is the cost function, α and β are hyper-parameters with the ratio α/β controlling the effective complexity of the network structure. The use of the hyper-parameters in the cost function can prevent the network trapped in poor generalization. As result, for BNN training, a validation set is not needed. For updating the hyperparameters, the Bayesian regulation method is used as follows:

$$\alpha^{MP} = \frac{\gamma}{2E_W(w^{MP})}; \beta^{MP} = \frac{N-\gamma}{2E_D(w^{MP})} \quad (7)$$

where E_w refers to the sum square of weight function, E_w refers to the error function, γ refers the effective number of parameters, N refers the total errors number, and w^{MP} refers to the minimum point. At the final stage, the network structure of the highest log evidence value is chosen as the best optimal structure of the BNN. For the performance classification indicators, the sensitivity, specificity and accuracy are reported in this study.

III. Results

Initially, the collected EEG dataset for the pre-task (alert)comprised of matrix with dimension of 26×15000×65 (number of EEG channels × 30 seconds of data point with frequency of 500Hz × number of participants) for eyes closed and another 26×15000×65 matrices for eyes open. The same amounts were applied to the post-task (fatigue). These matrices were fed into the PCA process. The PCA produces eigenvectors and eigenvalues.

The variances captured for the corresponding PCs were calculated as well. An eigenvalues scree plot is shown in Fig. 3 as a plot of percent variance captured versus number of principal components. It can be seen that that with 3 PCs, it already covers more than 80% of the variance of the original 26 EEG channels data. More detailed information of the percentage of the total variance from each and cumulative PCs is given in Table 1. The contribution of 10 PCs was shown in the descending order from the top to bottom. The 1st PCs contributed the highest data variance of 60.3% while the 10th PC contributed only 0.8%. For cumulative PCs contribution, the combination of three PCs already contributed a percentage data variance of 82.6%. This study applied a threshold of 90% of PCs to be used for further processing, in this case, up to 6 PCs were needed resulting in a total variance explained of 90.7%. The 6 PCs are the chosen component to generate the orthogonal transformation of the original 26 EEG channel.

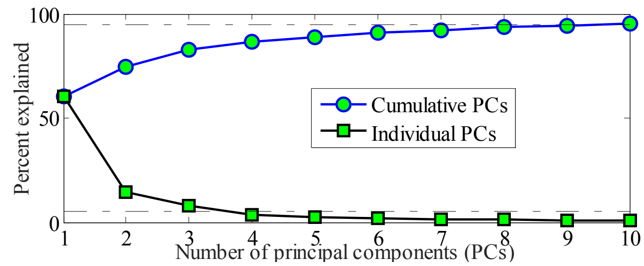

Figure 3. Scree plot of the pricipal components (PCs)

TABLE I. Percentage of total variability from each and cumulative principal components (PCs)

PCs number	% variance from individual PCs	% variance from cumulative PCs
1st PC	60.3%	60.3%
2nd PC	14.4%	74.7%
3rd PC	7.8%	82.6%
4th PC	3.8%	86.4%
5th PC	2.3%	88.7%
6th PC	**2.0%**	**90.7%**
7th PC	1.5%	92.2%
8th PC	1.3%	93.6%
9th PC	0.9%	94.5%
10th PC	0.8%	95.3%

After applying the PCA, the original high dimension of the EEG dataset was reduced from 26×15000×65 (number of channels × duration of data × number of participant) into a low dimension of 6×15000×65 (number of PCs × duration of the data × number of participants. Such a reduced dataset dimension results in a lower computational complexity.

Next, the dataset was fed into a moving window segmentation of 2s window with overlapping 1.5s for the 30s eyes open and eyes closed datasets of pre-task (alert) and post-task (fatigue) data group from the 65 participants. This provided 57 overlapping segments from each participant, or 3705 segments from the 65 participants. As a result, for the eyes open data, 3705 units for alert state and another 3705 units for a fatigue state were obtained. The dimension of the dataset after the segmentation is 6 × 3705 for the alert state and another 6 × 3705 for the fatigue state. The same dataset dimension was obtained for the eyes closed dataset. The PSD was used next to convert 2s segments into a frequency domain and a total PSD of 4 EEG band (delta, theta, alpha and beta) was calculated. With the 6

PCs this resulted in dimension of 24× 3705 for each alert and fatigue stage. For comparison, classification for the features from original 26 EEG channels without the use of PCA was also reported. The original 26 EEG data with dimension of 26×15000×65 were fed to segmentation and features extraction (PSD) processes which resulted features with dimension of 104 × 3705 (26 channels by 4 EEG bands × 2s windows segments).

For the BNN classifier training, the dataset was divided into half portions to act as a training set and another half portions for the testing set. The log evidence of BNN plotting for optimum structure of the network (log evidence against optimum hidden nodes number is shown in Fig. 4. The optimum number of hidden nodes for classification fatigue vs. alert was 16 for eyes closed and 14 for eyes open.

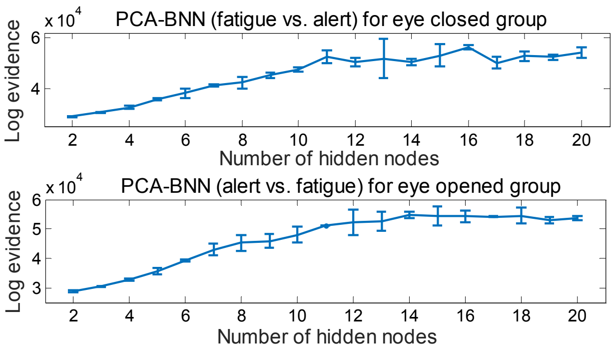

Figure 4. Log evidence from the BNN classifier training

TABLE II. THE RESULT OF PCA-BNN FOR FATIGUE VS. ALERT CLASSIFICATION AND COMPARISON WITH NO PCA USED

PCA/ Non-PCA used	Eyes Closed/Opened	Sensitivity	Specificity	Accuracy
PCA (only 6 PCs)	Eye Opened	76.8%	75.1%	76%
No PCA (32 channels)	Eye Opened	83.3%	68.2%	75.7%
PCA (only 6 PCs)	Eye Closed	76.1%	74.5%	75.3%
No PCA (32 channels)	Eye Closed	79%	71.5.2%	75.2%

The classification result tabulated in Table 2 reveal two groups: during eyes open and during eyes closed of fatigue vs. alert classification. During eyes open fatigue vs. alert classification, the PCA-BNN resulted in a sensitivity of 76.8%, a specificity of 75.1% and an accuracy of 76%, while the original 26 EEG channels (without PCA) resulted in a sensitivity of 83.3%, a specificity of 68.2% and an accuracy of 75.7%. During eyes closed fatigue vs. alert classification, the PCA-BNN resulted in a sensitivity of 76.1%, a specificity of 74.5% and an accuracy of 75.3%, while the original 26 EEG channels (without PCA) resulted in a sensitivity of 79%, a specificity of 71.5% and an accuracy of 75.2%. From this classification result, the PCA reduced the dimension of the dataset successfully for both eyes closed and eyes open data, and furthermore, resulting in a comparable accuracy to the dataset without the use of PCA. Moreover, this classification validates the use of the PCA-BNN for pre-task as fatigue data vs. post task (alert) classification with an accuracy around 75%, which involved of series eight mental load tasks. This also validates the series eight mental tasks for successfully inducing mental fatigue during the experiment.

IV. CONCLUSION

In this study, PCA was successfully applied for dimension reduction from an original 26 EEG channels of dataset into 6 principal components which still retained its information of above 90% from the original data. Feature extraction based PSD was applied and BNN used for classification between the fatigue and alert states with the dimension of 24× 3705. For comparison, the features of PSD were extracted from the original 26 EEG channels without the PCA method with dimension of 104 × 3705. Data also collected during eyes opened and closed validated fatigue status. The results suggest that PCA-BNN provides a comparable result in term of accuracy to dataset from original 26 EEG channels (without PCA) for classifying fatigue vs. alert states during eyes opened and closed periods. This demonstrates the capability of PCA in terms of dimension reduction which contributes to reducing computational complexity, a valuable findings if such an approach were to be used in real time monitoring of fatigue. The results also validate the use of the series mental work load in this study for inducing mental fatigue with classification accuracy around 75% (pre-task/fatigue vs. post-task/alert).

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