Classification of Driver Fatigue in an Electroencephalography-based Countermeasure System with Source Separation Module

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***Abstract*— An electroencephalography (EEG)-based counter measure device could be used for fatigue detection during driving. This paper explores the classification of fatigue and alert states using power spectral density (PSD) as a feature extractor and fuzzy swarm based-artificial neural network (ANN) as a classifier. An independent component analysis of entropy rate bound minimization (ICA-ERBM) is investigated as a novel source separation technique for fatigue classification using EEG analysis. A comparison of the classification accuracy of source separator versus no source separator is presented. Classification performance based on 43 participants without the inclusion of the source separator resulted in an overall sensitivity of 71.67%, a specificity of 75.63% and an accuracy of 73.65%. However, these results were improved after the inclusion of a source separator module, resulting in an overall sensitivity of 78.16%, a specificity of 79.60% and an accuracy of 78.88% ($p < 0.05$).**

I. Introduction

Fatigue refers to a mental state involving psychological and/or physical tiredness. In the transportation industry, it is reported that fatigue reduces the ability to perform a task and could lead to potential serious problems and injuries [1]. Moreover, fatigue is a major contributor to injury, and believed responsible for around 14-20% of serious crashes and fatalities in road accidents [1]. Thus, driver fatigue is dangerous not only for drivers but also potentially harmful for other road users. As a result, an automatic countermeasure system capable of detecting decreasing alertness and increasing fatigue would be an important strategy for the improvement of road safety.

Currently, approaches used for fatigue measurement include: (i) self-report of fatigue; (ii) electrocardiography (ECG) and heart rate variability monitoring; (iii) electrooculography (EOG) monitoring to capture eye movements and blink activity; (iv) electroencephalography (EEG) monitoring for brain wave analysis [2]. Self-reporting fatigue using a psychometric/questionnaire approach would be cumbersome as the basis for a continuous countermeasure fatigue monitoring system, as it would be time consuming and highly subjective strategy. However, methods using ECG, EOG and EEG psychophysiological measurements are promising fatigue detection techniques. EOG measures changes in eye activity associated with fatigue, ECG measures change in heart rate activity associated with fatigue, while EEG measures change in brain activity associated with fatigue. EEG is also popular in sleep studies, as it correlates with brain activity directly [3]. Moreover, fatigue can also be viewed as an early phase of sleepiness, occurring just before of the onset of microsleep [4]. EEG is also considered a promising method for an automatic countermeasure fatigue system [5, 6]. This study explores the classification of fatigue using EEG signals.

Generally, the classification of EEG analysis involves signal acquisition, signal pre-processing, feature extraction and feature classification [7]. The signal pre-processing covers artifacts and noise reduction and data segmentation. The popular feature extraction in EEG analysis which has been widely used for study of fatigue is based on power spectral density (PSD) [8]. For the classifier, linear and non-linear classification algorithms can be used. Artificial neural network (ANN) based-classification is popular for biomedical applications [9]. Moreover, ANN with fuzzy particle swarm optimization has been used for the classification of mental tasks in brain computer interface (BCI) applications [10].

EEG contains a high temporal resolution of brain signals where multiple neural generators can be activated at the same time. As a result, multivariate methods such as independent component analysis (ICA) can be used to extract the complex connections of the dependent and independent parameters or as a source separator of the EEG data [11]. In the past, ICA has been widely used for EEG artifacts removal [12]. Recently, ICA using entropy rate bound minimization (ERBM) has been introduced for blind source separation techniques [13]. This paper investigates the classification between fatigue and alert states with the inclusion of additional source separator components using the latest independent component analysis, that is, ICA-ERBM. The result is compared with the conventional component of classification which does not contain the source separator module.

II. Methodology

A. Components for Fatigue Classification

The components for the EEG-based fatigue classification method are shown in Fig.1, beginning with the assessment

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of EEG during a driver fatigue experiment. Using the data from this fatigue study, the process is continued with a pre-processing module for removing noise and artifact. A new component called “source separation” is added by using latest source separation technique, ICA-ERBM. The window segmentation is applied to the data from the source separator. Each of the data segments is fed to the feature extraction before continuing with the classification process. The output of the classifier is either a fatigue or alert state.

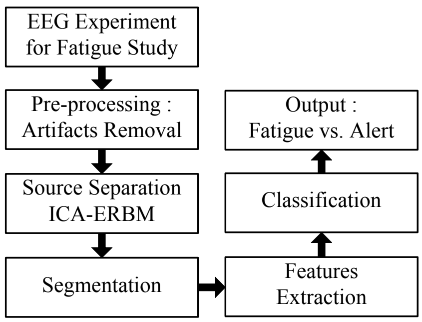

Figure 1. Components for EEG-based fatigue classification

B. Data Collection and Pre-processing

The driver fatigue experiment involved 43 adults (18-55 years) participating in a simulated driving task [8]. The study was approved by a University Research Ethics Committee. The divided attention steering simulator (DASS) was used for driving simulation [8]. Participants were asked to drive in the center of the road slowly at speeds of 40-60 km/hr until signs of fatigue occurred. Participants also needed to respond to a target number that appeared randomly on the computer screen and their reaction times were measured. The experiment was terminated when: (i) signs of facial fatigue occurred such as head nodding and extended eye closure, (ii) the participant deviated off the road for more than 15 seconds, and (iii) a two hours maximum driving time applied if the participants did not show fatigue signs or deviated off the road during the experiment.

In this experiment, brain activity was recorded using 32 channels of EEG (Active-Two system from Biosemi) with sampling rate set at 2048 Hz and electrode positions were: FP1, AF3, F7, F3, FC1, FC5, T7, C3, CP1, CP5, P7, P3, PZ, PO3, O1, OZ, O2, PO4, P4, P8, CP6, CP2, C4, T8, FC6, FC2, F4, F8, AF4, FP2, FZ and CZ. Also EOG signals were recorded for the detection of eye closure and video recording of the participant’s faces was conducted for fatigue verification. Fatigue status was verified by checking the eye closure time from the EOG signal and from facial signs from the recorded videos, including extended eye closure, increased eyes blink rate, nodding of the head, yawning and performance of driver error such as deviating off the road.

The sampling rate of the EEG data was down sampled from 2048Hz to 256Hz which was used for the remaining analyses. In the pre-processing step, in order to remove eyes blink, muscle and heart artifact, a method based on the second order blink identification (SOBI) and canonical correlation analysis was applied to the raw EEG data [14]. The cleaned EEG data as shown in Fig. 2 was divided into alert and fatigue groups. The first five minutes of the EEG data from the beginning of the driving task was used for the alert data. The last five minutes before the task was stopped was used for fatigue data. Further, in each group of data, a 20 second segments containing the least movement artifact was used for further processing, in this case the source separation module.

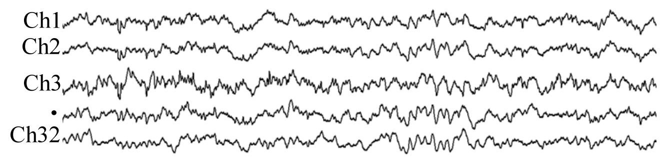

Figure 2. EEG data after pre-processing

C. Source Separation

In the source separation module an ICA-based method was used with comparisons made to the conventional EEG classification environment. Most existing ICA methods use second order and higher order statistics for minimizing the source of non-Gaussianity. The ICA using EBRM, introduced recently, manages both non-Gaussianity and sample correlation by maximizing mutual information rate [13, 15]. Let, a statistically independent, zero mean source $s(t)=[s_1(t),\ldots,s_N(t)]^T$ be mixed with an $N \times N$ mixing matrix A such that we obtain the mixture $x(t)=[x_1(t),\ldots,x_N(t)]^T$ as $x(t)=As(t)$, where T and t denote the transpose and time index respectively. ICA separates the mixture using $y(t)=Wx(t)$ where $y(t)=[y_1(t),\ldots,y_N(t)]^T$ and W is the unmixing matrix. ICA assumes that the sources are identically distributed, hence, a cost for achieving the separation of these N independent sources is the mutual information $I(y_1;,\ldots,;y_N)$ among N random variables y_n, $n=1,\ldots,N$, which is:

$$I(y_1;,\ldots,;y_N)=\sum_{n=1}^{N}H(y_n)-\log\left|\det(W)\right|-H(x) \quad (1)$$

where $H(y_n)$ represents the entropy of the nth individual source. However, a new cost function needs to be added since, the equation (1) cannot exploit the temporal structure of sources. The new cost function is given as

$$I_r(y_1;,\ldots,;y_N)=\sum_{n=1}^{N}H_r(y_n)-\log\left|\det(W)\right|-H_r(x) \quad (2)$$

where $H_r(y_n)$ is the entropy rate of the n[th] process of y_n. The equation (1) is modified to obtain new entropy and cost function as given in equation (2). More information about the ICA-ERBM can be found in [13].

D. Segmentation and Features Extraction

The output from the source separation was segmented before applying a feature extraction algorithm by using 2 seconds of moving window with an overlapping of a quarter of a second, providing 73 units of segments. The total of 43 participants provided 3139 units of segments for the alert state and another 3139 units of segment for the fatigue state. This is continued by applying the feature extractor based on power spectral density (PSD). This involves conversion of the time domain of the EEG data from the previous process into frequency domain, covering the four EEG bands which include delta bands (δ) from 0.5Hz to 3Hz, theta (θ) from 3.5Hz to7.5Hz, alpha (α) from 8Hz to13Hz and beta (β) from 13.5Hz to30Hz. For the features, the total power for each band was determined by using the numerical integration of trapezoidal rule. With the 4 EEG bands in 32 EEG channels, it provided a total of 128 units which was used as the input features of the classifier.

E. Classification

For the classifier, the ANN method used is a popular technique to solve non-linear classification problems [9]. The classifier is combined with optimization techniques known as fuzzy particle swarm optimization with cross-mutated operation (FPSOCM), and which has been used in a previous study for EEG classification of mental tasks [10].

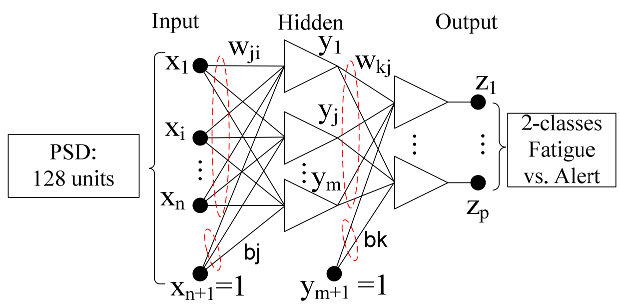

Figure 3. The structure of ANN for fatigue vs alert classification

The structure of the ANN is shown in Fig. 3 which is a three layers feed- forward structure configuration. Prior the process of the ANN training, the features were normalized into [0 1]. The model of the ANN is as follow:

$$z_k(x,w) = f_1\left(b_k + \sum_{j=1}^{m} w_{kj} f_2\left(b_j + \sum_{i=1}^{n} w_{ji} x_n^*\right)\right) \tag{3}$$

where *f(.)* denotes the transfer functions of ANN, in this paper, the log-sigmoid was used, where *m* denotes the number of input nodes, *l* denotes the number of hidden nodes, *p* denotes the number of outputs, w_{ji} refers to the weight to the hidden unit y_j from input unit x_i, i=1, 2, …, m, *and* j=1, 2, …, l, w_{kj} refers the weights to output (z_k) from hidden unit (y_j), k=1, 2, …, p, b_j and b_k refer to the biases. The normalization is as follow:

$$X^* = (X - X_{min}) / (X_{max} - X_{min}) \tag{4}$$

where X^* denotes the output value after normalization. X denotes the output value before normalization. X_{min} denotes the minimum feature value and X_{max} is the maximum feature value. For the FPSOCM, a fuzzy inertia weight and cross-mutated operation were calculated for improvement of the performance searching and also to solve the conventional issue of the local optima trapping.

III. Results

Fig. 4 shows the comparison of the power spectrum plotting between the fatigue and alert states using the 20s durations of data from the source separator, ICA-EBRM. From Figure 4, it can be seen there are changes of higher power spectrum value from the fatigue data compared to the alert data. The alpha band (8-13Hz) and beta band (14-30Hz) shows a significant change in the fatigue data as compared to the alert data.

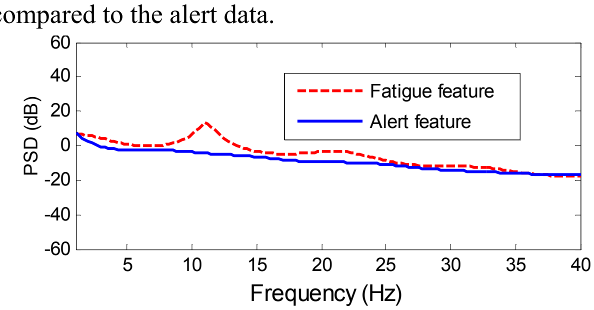

Figure 4. Comparison PSD plotting between fatigue and alert

The training of the ANN optimized by FPSOCM was repeated 10 times for each different hidden neuron. As a result, the average value of 10 results of accuracies was used. The number of hidden neurons varied from 4 to 30 units to obtain the best number which provides the highest classification accuracy. The parameters for FPSOCM optimizer were: the size of the swarm was 50, the numbers of iterations 10000, the acceleration constants were 2.05, the maximum velocity 0.2 and probability of each cross mutated was 0.0005. A total of 3139 units of datasets for the alert state and another 3139 units for the fatigue state of 43 participants were divided into 3 datasets including: a training set which had 1032 units, a validation set which had 1032 units and a testing set which had 1075 units.

The performance measurement indicators sensitivity, specificity and accuracy were calculated. To avoid the over-fitting problem, a widely used early stopping method was used. As a result, the data was divided into training, validation and testing sets. The final performance result is based on the testing set. The classification result is shown in Table I which includes the classification without the inclusion of the source separator module and the classification with the ICA-ERBM (source separator module). The results for the classification without using the source separator are: for the training set, the average sensitivity was 83.35%, the specificity was 85.31% and the accuracy was 85.33%. For the validation set, the average sensitivity was 78.18%, specificity was 80.98% and accuracy was 79.58%. The overall result for the testing set are: sensitivity was 71.67%, specificity was 75.63% and accuracy was 73.65%. This classification result is improved with the addition of the source separator algorithm and the results are as follows: for the training set, the average sensitivity was 85.76%, the specificity was 88.08% and accuracy was 86.92%; for the validation set, the sensitivity was 83.43%, specificity was 84.79% and accuracy was 84.11%. For the testing set, the sensitivity was 78.16%, specificity was 79.60% and accuracy was 78.88%.

TABLE I. RESULT CLASSIFICATION OF FATIGUE VS. ALERT OF 32 EEG CHANNELS FROM 43 SUBJECTS.

Method	**Dataset**	**Correctly Identified**		**Accuracy (%±sd)**
		Fatigue	**Alert**	
		Sensitivity (%±sd)	**Specificity (%±sd)**	
(i) Result classification without the inclusion of source separator	Training	83.35±3.25	87.31±2.56	85.33±2.05
	Validation	78.18±2.41	80.98±2.36	79.58±1.57
	Testing	**71.67±1.83**	**75.63±2.18**	**73.65±1.48**
(ii) Result classification with the inclusion of Source Separator of ICA-ERBM	Training	85.76±1.81	88.08±1.11	86.92±1.12
	Validation	83.43±2.39	84.79±1.73	84.11±1.64
	Testing	**78.16±2.04**	**79.60±2.35**	**78.88±1.84**
p-value (i) vs. (ii)	**Testing**	0.000000016 (<0.05)	0.00043 (<0.05)	0.00000043 (<0.05)

Overall, comparing results of the testing set (for performance estimation of unseen dataset) to the results without the inclusion of the source separator compared to the result with the inclusion ICA-ERBM (source separator) are: an improved sensitivity of 6.49% (from 71.67% to 78.16%), an improved specificity of 3.97% (from 75.63% to 79.60%) and an improved accuracy of 5.23% (from 73.65% to 78.88%). A statistical test between the overall accuracy between classification without the inclusion of source separator and the classification with the inclusion of source separator resulted in significance at a *p*-value less than 0.05. This indicates that the performance of the classification with source separator is significantly better than the classification without source separator with a 95% confidence level.

IV. CONCLUSION

In this paper, the ICA-ERBM source separator was investigated as a new component for an EEG-based classification of fatigue and alert states. After the process of the source separation, the feature extractor (PSD) and classifier ANN with the PSOCM were used. The plotting of the power spectrum showed a distinction between the fatigue state and alert state especially within the alpha and beta band. The performance results of the classification were improved after applying the source separator module compared to the result without the inclusion of the source separator. The overall results without the source separator includes: a sensitivity of 71.67%, a specificity of 75.67% and an accuracy of 76.65%. This result was improved with the inclusion of the source separator (ICA-ERBM) which includes: a sensitivity of 78.16%, a specificity of 79.60% and an accuracy of 78.88%. The comparison was significant at $p<0.05$. Future direction and work includes improving the classification accuracy further by optimizing features as well as improving the ICA algorithm. Such improvements in sensitivity, specificity and accuracy may well lead to real time fatigue monitoring using brain wave signals with concomitant improvement in road and work context safety.

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