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Classifying Driving Fatigue Based on Combined Entropy Measure Using EEG Signals

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Abstract

Driving fatigue is a common occupational hazard for any long distance or professional driver, and fatigue detecting has major implications for transportation safety. Monitoring physiological signal while driving can provide the possibility to detect the fatigue and give the necessary warning. In this paper, fifty subjects participated in driving simulations experiment with their recorded EEG signals to induce two kinds of fatigue states: Alert and drowsy. Two nonlinear methods, approximate Entropy (AE) and Sample Entropy (SE), were used to characterize irregularity and complexity of EEG data. Subsequently Support Vector Machine (SVM) was applied to classify these two fatigue states. The experimental result shows that two complexity parameters are significantly decreased as the fatigue level increases. The result indicates that both of two nonlinear indicators can be used to characterize driver fatigue level. Furthermore, the combined measure feature results in higher classification accuracy, indicating the proposed classification method is more robust and effective, compared with single complexity measure.

Keywords: *Driver fatigue; approximate entropy (AE); sample entropy (SE); Electroencephalogram (EEG)*

1. Introduction

Fatigue is a common occupational hazard for any long distance or professional driver, and can affect driver's ability to continue driving [1]. Fatigue is a complex state which manifests itself in the form of lack of alertness and reduced mental performance, often accompanied by drowsiness [2]. Driver fatigue frequently occurs and is believed to be responsible for 20–30% of road related accidents. Driving fatigue is widely recognized as a core safety issue in the transportation. When people become fatigued, they usually experience difficulties in maintaining task performance at an adequate level [3]. The detection and quantification of fatigue can help researchers to build instruments that will help in early assessment of fatigue level on-board. Therefore, many researchers proposed various methods to estimate the driver fatigue. One approach monitors driver or vehicle physical changes such as the inclination of the driver's head, sagging posture, and open/close state of the eyes, decline in gripping force on steering wheel, vehicle lateral

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position, vehicle speed and vehicle yaw rates [4-5] The other approaches focus on the fields to measure physiological changes such as eye-blinking, heart-rate, pulse-rate or skin electric-potential, particularly, brain waves, as a means of detecting a human fatigue state. Among a number of physiological indicators available to measure fatigue, the electroencephalographic (EEG) is widely considered to be the most significant and reliable indicator of fatigue [6-8].

In recent years, EEG signals were widely used to detect fatigue [9-12]. Driving involves various functions such as movement, visual and auditory processing, decision making and recognition. EEG is generated by cell bodies and dendrites of neurons [2] and closely associated with mental and physical activities, which is influenced by psychological factors. Hence, all the physical and mental activities associated with driving are reflected in EEG signals.

A number of methods for driving fatigue detection using EEG have been proposed, such as the assessing methods based on the frequency domain information detection of alpha spindles by Tietze [13], and an algorithm that utilizes the combination of all frequency components of EEG to signify level of alertness by Lal [5, 14].

Up to the present, few studies used nonlinear measure to assess driver fatigue [15]. Azarnoosh used Symbolic dynamics indictor to assess fatigue [16].

Here in order to study the sensitivity of nonlinear complexity measures to driver fatigue, two complexity parameters, Sample entropy (*SE*) [17-18] and approximate entropy (*AE*) [18-19], were used to quantify the complexity and irregularity of EEG data under a driver fatigue state, i.e., before and after performing a 2-hours driving task. Subsequently, Support Vector Machine (SVM) [21-22], a nonlinear classification tool, was used to identify the state of driver fatigue from the non-fatigue (alert) state.

Up to now, to the best of our knowledge, there is no study in the literature related to the assessment of classification performance using *AE* or *SE*-based feature extraction and SVM classifier when applied specifically to the driving fatigue problem. Experimental results indicate that, compared with several previous studies, the proposed method could enhance the detection rate. Figure 1 shows the schematics of the proposed diagnosis expert system.

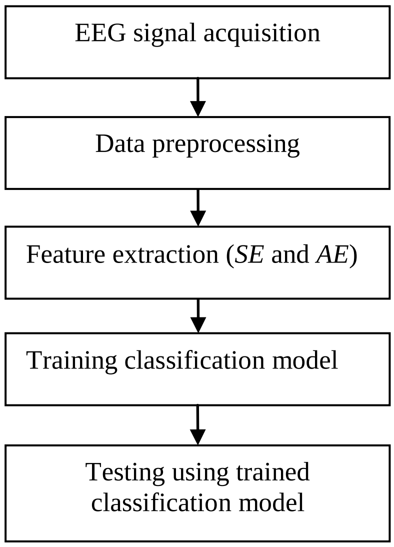

Figure 1. The Proposed Classification Model For Classifying Driving Fatigue.

2. Materials and Methods

2.1. Subject

Sixty graduate students (25 females, aged 19-23 years, mean: 21) were chosen from the university and recruited to perform monotonous driving simulator task. All subjects were in good health and have no disorders related to sleep. The participants were asked to refrain from any type of medicine and stimulus like alcohol or coffee during the experiment. None of them had taken any drugs and reported on any cardiovascular disease or neurological disorders in the past. This study had the institute's Human Research Ethics Committee approval. The Participants provided their written informed consent according to a human research protocol in this study. They did not work night shifts and had normal sleep time.

2.2. Data Acquisition

All the subjects were seated on a chair, facing a video screen 1m from their eyes. EEG was recorded on the following silver electrodes: Fp2, Fp1, F4, F3, Fz, C4, C3, P4, P3, Cz, Pz, and Oz, based on the international 10-20 system. The vertical electrooculography (VEOG) signals and the horizontal EOG (HEOG) signals were also recorded. EEG and EOG signals were filtered through Neuroscan Synamps Amplifier with a band pass filter of 0.01-100Hz, and digitized at 500Hz. EOG was used to analyze eye blink patterns as part of the manual classification criteria for classifying EEG alertness and drowsiness. All electrodes were referenced to the right earlobe and the electrode impedances were less than 2 kW. Eye movement artifacts were removed from EEG signal by the adaptive filter based on least mean square algorithm. The artifacts removal criterion was ±75μv. Artifact rejection is done by visually inspecting the EEG.

First, subjective sleepiness was assessed by means of the Stanford Sleepiness Scale and the Karolinska sleepiness scale, and subjective fatigue was measured with the help of the Samn-Perelli checklist, Li's subjective fatigue scale and Borg's CR-10 scale [23]. Subsequently, participants completed the first session. This is a 15min alert driving session, during which, participants were faced on a road involving many cars and stimuli. We set this recording as a baseline measure. After the recording, the 15min EEG were divided into many 10s epoched EEG dataset by EEGLAB toolbox. We labeled them as alert EEG. Hence, there were totally 50*15*60/10=4500 epoched alert datasets for further processing.

2.3. Driving Simulation Task

Following the alert driving session was the monotonous driving session, in which, each subject performed simulated driving test. The participant operated car and acted as drivers on a simulated driving platform. At the same time, a video clip showing moving road images of only straight highways mostly free of vehicles was displayed in the screen of the driving platform. Each subject was asked to watch the road at all times. The driving lasted 2-3h until we have observed obvious drowsy EEG for at least 15min. The last 15min EEG signal was divided into many 10s epoched EEG dataset. We labeled them as drowsy EEG.

2.4. Data Preprocessing

Epoch was labeled as alert or drowsy classes by one independent psychophysiologist who has trained in interpreting the EEG. The identification criterion was based on two indexes [24]: (1) eye blink patterns and (2) dominant EEG frequency component. The alert state is dominated by beta component (13-25Hz), eye blinks of 0.3–0.4s durations [25] and inter-eye blink intervals of 6-8s [26]. The drowsy state will show frequent slow eye movement with dominant alpha rhythm (9-13Hz), duration time of eye closures greater than 0.5s. The epochs with ambiguities were excluded from the analysis. Finally, we selected 4000 drowsy and 4000 alert datasets for further feature extraction.

2.5. Feature Extraction

Entropy is a concept handling predictability and randomness, with higher values of entropy always related to less system order and larger randomness [27]. In recent years, researchers proposed various estimators to quantify the entropy of time series. These estimators can be roughly divided into m bedding entropy and spectral entropy [28]. Embedding entropy assess how EEG time series signals change with time by comparing each time series signal with a lagged form of itself [29].

In this paper, Two *m* bedding entropy-based complexity parameters: *AE* and *SE* are used to quantify the complexity of EEG under two driver fatigue states. Compared with other non-linear dynamics parameters, *AE* is less sensitive to noise and can be applied for short-length time series data. For calculating the *AE*, the embedding dimension (*m*) and vector comparison threshold (*r*) must be specified. The value of *AE* is determined in the following steps:

The value of *AE* is determined in the following steps:

Given a time series $\{\{x(n)\} = x(1), x(2), ..., x(N)\ \}$ with N data points, take m vectors $X_m(1), ..., X_m(N-m+1)$ defined as $X_m(i) = [x(i), x(i+1), ..., x(i+m-1)]$, $1 \le i \le N-m+1$.

Two input parameters *m* and *r*, must be fixed before calculating *AE*, in which *r* denote the noise filter level and is defined as:

$$r=g*SD \;\; for\; g=0.1,0.2,...,0.9 \tag{1}$$

Where *SD* represents the standard deviation of the data sequence *X*

Define the distance between X(*i*) and X(*j*), d[X(*i*),X(*j*)] as follows:

$$d[X_m(i), X_m(j)] = \max_{k=0,...,m-1}(|x(i+k) - x(j+k)|) \tag{2}$$

For a given $X_m(i)$, count the number of *j* (1<*j*<*N* –*m*+1), so that $d[X_m(i), X_m(j)] < r$, denoted $N^m(i)$.

Then, for $1 \le i \le N-m+1$, calculate:

$$C_r^m(i) = N^m(i)/(N-m+1) \tag{3}$$

Define $\Omega^m(r)$ as

$$\Omega^m(r) = \frac{1}{N-m+1}\sum_{i=1}^{N-m+1} \ln C_r^m(i) \tag{4}$$

Finally, calculate *AE*

$$APEN(m,r,N) = \Omega^m(r) - \Omega^{m+1}(r) \tag{5}$$

The *AE* algorithm counts each sequence as matching itself to avoid the occurrence of ln(0) in the calculations. To reduce this bias, Richman and Moorman have developed and characterized a new family of statistics: *SE*. *SE* is the negative logarithm of the conditional probability that two sequences similar form points remain similar at the next point, where self-matches are not included in calculating the probability. Thus, a lower value of *SE* also indicates more self-similarity in the time series [29].

The value of *SE* is determined in the following steps:

Given a time series $\{\{x(n)\} = x(1), x(2), ..., x(N)\ \}$ with N data points, take m vectors $X_m(1), ..., X_m(N-m+1)$ defined as $X_m(i) = [x(i), x(i+1), ..., x(i+m-1)]$ for $1 \le i \le N-m+1$.

Similar to *AE* algorithm, two parameters *m* and *r* were also fixed before calculation, in which *r* denote the noise filter level and is defined as:

$$r=g*SD \text{ for } g=0.1,0.2,...,0.9 \quad (6)$$

Subsequently, define the distance between X(i) and X(j), d[X(i),X(j)] as follows:

$$d[X_m(i),X_m(j)] = \max_{k=0,...,m-1}(|x(i+k)-x(j+k)|) \quad (7)$$

For a given $X_m(i)$, count the number of *j* (1<*j*<*N* –*m*, $j \neq i$), so that $d[X_m(i),X_m(j)] < r$, denoted as B_i.

Then, calculate:

$$B_i^m(r) = \frac{1}{N-m+1} B_i \quad (8)$$

Define $B^m(r)$ as

$$B^m(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} B_i^m(r) \quad (9)$$

Similar to the calculation of *AE* algorithm increment the dimension to *m* = *m* + *1* and compute $B^{m+1}(r)$, Finally, calculate *SE as*

$$SE(m,r) = \ln \frac{B^{m+1}(r)}{B^m(r)} \quad (10)$$

SE is first analyzed as feature extraction methods for evaluating the regularity of the epileptic EEG signals [30].

By above feature extraction, 4000 drowsy and 4000 alert 2-dimensional feature vectors were fed into the classifier to train and test.

2.6. Classification

In this study, SVM was used for the purpose of automatic classification between alert and drowsy EEG epochs after above feature extraction. The goal of SVM is to find an optimal hyperplane that maximizes the separating margin between ω_1 and ω_2. It is solved by the following minimization procedure with a constraint condition:

$$\min(C\sum_{i=1}^{k}\gamma_j + \frac{1}{2}\|\vec{W}\|^2) \qquad i = 1, 2, \dots, k \quad (11)$$

where $l_i \in \{\pm 1\}$ is the class label of the *i*th sample with *k* being the number of SV. g_i denotes the feature vector of the *i*th sample; $\vec{W}$ and *b* denotes the orientation and offset of the hyperplane, respectively. $\|\vec{W}\|^2$ is used to calculate the squared Euclidean norm, $(\square)$ denotes the dot product. γ_i is called slack parameter. *C* is a penalty factor and can be determined by the cross validation procedure. Above optimization problem can be solved by introducing the other optimization for Lagrangian multipliers α_i. A sample g_i is a Support Vectors (SV) when it corresponds to a nonzero α_i. Let g_i^s denote a SV, and then the class label of any test sample *g* can be given as followings:

$$l(g) = \text{sgn}(\sum_{i=1}^{k_s} l_i \alpha_i K(g_i^s, g) + b) \quad (12)$$

where K_s is the number of SV. "sgn" denotes a flag function which transforms a negative input value to -1 and positive value to 1. Notation K denotes a kernel function which is used to project the samples to a new feature space with a higher dimension where the samples can be linearly separated. In this study, related parameter values in the kernel function were also determined by cross validation procedure.

In this study, SVM toolbox using Matlab was applied. The SVM performance was assessed on both the training and the testing sets. 10 fold cross validation was used.

3. Result

AE and *SE* (m = 1, r = 0.2 times the standard deviation of the data) were estimated for all the channels. Table 1 shows the averaged *AE* and *SE* across on all the epochs. The *AE* and *SE* values (mean ± SD) for the alert and drowsy states and the p values of the t-tests performed to examine the differences between the two states. Related results are summarized in Table 1. It can be seen there is no significant differences both for *AE* and *SE* measures at most of channels except Pz, P3, Pz and Oz, although most entropy values for drowsy are smaller than those for alert state.

Furthermore, above 4 electrodes were selected and classification performance (testing accuracy) for combined entropy measures was evaluated. Table 2 summarizes classification accuracy of the EEGs for the drowsy (sensitivity) and alert (specificity) states only for above 4 electrodes. The highest sensitivity was obtained at electrode P3 (93.67%), although with a small specificity (88.89%). The highest specificity was reached at electrode P4 (91.11%). Finally, the averaged accuracy is highest at P3 electrode in which significant differences between two states is 0.022 for *AE* and 0.026 for *SE*.

For one thing, we found most *AE* and *SE* values of drowsy state are smaller than those of alert. It is noted that one cannot obtain high classification accuracy using single complexity measure, which can be seen for p values in Table 1. However, when using combined complexity measure and machine learning method, classification accuracy reach a satisfactory level after our training and testing. Finally, high classification accuracy indicates SVM is suitable for classifying two different fatigue states.

Table 1. *AE* And *SE* Values With Corresponding Significant Difference Level (*P* Value) Between Alert And Drowsy States

Channels	*AE* for alert (mean ± SD)	*AE* for drowsy (mean ± SD)	Statistical analysis (p value for *AE*)	*SE* for alert (mean ± SD)	*SE* for drowsy (mean ± SD)	*Statistical analysis (p value for SE)*
FP2	0.651 ± 0.133	0.565 ± 0.147	0.234	0.671 ± 0.243	0.668 ± 0.173	0.132
Fp1	0.562 ± 0.166	0.549 ± 0.173	0.461	0.621 ± 0.134	0.632 ± 0.177	0.509
F3	0.587 ± 0.211	0.623 ± 0.081	0.286	0.771 ± 0.117	0.700 ± 0.165	0.343
F4	0.724 ± 0.211	0.713 ± 0.135	0.212	0.730 ± 0.153	0.711 ± 0.281	0.423
Fz	0.735 ± 0.133	0.721 ± 0.209	0.432	0.765 ± 0.161	0.750 ± 0.202	0.521
C4	0.661 ± 0.134	0.637 ± 0.180	0.342	0.687 ± 0.154	0.655 ± 0.214	0.585
C3	0.637 ± 0.156	0.635 ± 0.146	0.332	0.588 ± 0.245	0.538 ± 0.163	0.476
Cz	0.600 ± 0.133	0.585 ± 0.136	0.297	0.660 ± 0.270	0.685 ± 0.157	0.465
P4*	0.674 ± 0.154	0.554 ± 0.188	0.035	0.612 ± 0.158	0.593 ± 0.128	0.030
P *	0.715 ±	0.665 ± 0.	0.021	0.689 ±	0.584 ± 0.	0.026
P *	0.682 ±	0.554 ± 0.	0.043	0.583 ±	0.509 ± 0.	0.034
O *	0.680 ±	0.582 ± 0.	0.033	0.675 ±	0.576 ± 0.	0.033

* denotes p value is less than 0.05

Table 2. Classification Accuracy of the Eegs for the Drowsy (Sensitivity) and Alert (Specificity) for Four Channels Using Proposed Method

Channel	Sensitivity (%)	Specificity (%)	Averaged accuracy
P4	0.8855 ± 0.1289	0.9111 ± 0.1432	0. 8983
P3	0.9367 ± 0.1435	0.8889 ± 0.1700	0. 9128
Pz	0.9340 ± 0.1551	0.8788 ± 0.1562	0. 9064
Oz	0.8775 ± 0.2553	0.9012 ± 0.1536	0. 8893

4. Discussion

Fatigue is a prevalent and potentially dangerous transport related condition. In this study, two widely used complexity measure, *AE* and *SE*, were used to quantify the complexity of EEG between before and after driving fatigue. This study also aims to use SVM to establish an automatic method of distinguishing between alert and drowsy states, hence developing a reliable detection system of drowsiness for driving safety.

As nonlinear complexity measures, *AE* and *SE* could effectively reveal the regularity and randomness in a time varying EEG and obtain the information regarding the dynamics of the specific regional brain subsystem. We found significant difference mainly at parietal and occipital regions, which suggests EEG from the above two regions is sensitive for change of level of fatigue.

Long time of cognitive work would induce the increase of driver fatigue. Compared with single measure, the combination of the complexity parameters *AE* and *SE* of EEG can effectively characterize the fatigue degree during driver fatigue.

In this study, combining index of *AE* and *SE* shows a significant change after long time driving task. The results indicate that the subjects' alertness level declines greatly, and the excitement level of brain decreases after the completion of the task. Although non-linear EEG analysis has not yet been applied as a diagnostic tool, our study is very important from a theoretical point of view. It shows the possibility to analyze the dynamical behavior of the brain and to find differences between alert and fatigue states using the proposed non-linear measures. We believe they might be a powerful tool to reveal hidden characteristics of bio-signals which cannot be detected using linear analysis, as physiological systems are basically non-linear in nature. Also the proposed method will give us a deeper understanding of the brain function in ways which are not possible by the other conventional statistical or linear methods.

For driver fatigue classification, experimental results indicate that SVM method might be a useful classifier in the estimation of driver fatigue. Our experimental results also demonstrate that a high-dimensionality non-linear pattern classification method, SVM, is able to detect the complex patterns of brain activities relevant to the driving fatigue. We believe, this proposed method can be applied on board to quantify the level of fatigue in human drivers or human operators in safety critical human-machine interactions. It is noted that for SVM classifier, two classification parameters was simply assigned in this study by our experience. Obviously, more suitable tools for selecting the classifier parameter values such as LIBSVM package should be used to further enhance the performance of our method.

For this study, the high classification accuracy may possibly be achieved if less EEG channels were used. We used a full 14-channel EEG recording in this study. However, if viewed from an economic or ergonomic aspect with respect to product development, more EEG recording channels may not be feasible. Hence, Key EEG channel selection could be worthy of future investigations so that the optimal number of EEG channels can be determined.

In this study, the sample population of subjects has been restricted to young healthy subject in the university in an attempt to minimize the effect of individual differences. Since the study showed encouraging results for the automatic detection of drowsiness during driving, future studies should include a wide range of subjects to detect a possible effect of other variables such as age and driving experience.

Finally, using other classification method such as extreme learning machine to identify EEG with fatigue would be attempted in our future study. We believe it would enhance classification performance further.

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