EEG-Based Fatigue Classification by Using Parallel Hidden Markov Model and Pattern Classifier Combination

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Abstract. Fatigue is the most important reason leading to traffic accidents. In order to ensure traffic safety, various methods based on electroencephalogram (EEG) are proposed. But most of them, either regression or classification, are focused on the relationship between feature space and observation values, so the changing patterns of features are ignored or discarded. In this paper, we propose a new fatigue classification method by using parallel hidden-Markov-model and pattern classifier combination techniques, where each model represents a particular fatigue-high-related feature. In the experiment, subjects are asked to accomplish some simple tasks, and both their fatigue states and their EEG signals are recorded simultaneously. Experimental results indicate that the mean error rate obtained by using our new method are 11.15% for classifying 3 states and 16.91% for classifying 4 states, respectively, while the existing approach can only reach 16.45% and 23.55% under the same condition.

Keywords: EEG, Fatigue Classification, PHMM, Classifier Combination, Fuzzy integral.

1 Introduction

In recent years, the traffic safety is worrying because of the frequently happened traffic accidents and the great damage to people and economy. Among the numerous factors, fatigue driving is the most significant one [6,12]. Therefore many researchers are trying to develop a fatigue on-line estimating system with high time resolution and high accuracy. They have tried various signals including pulse, facial movement or other physiological signals. Among these signals, electroencephalogram (EEG) has been proved to be high correlated, accurate and

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reliable [7]. Meanwhile, many good characteristics of EEG have been pointed out, including the EEG spectrum whose principal component has the positive correlation with fatigue state. By using the EEG spectrum features, we proposed a method to solve these problems to some extent for fatigue classification.

The existing approaches suffer the following four main deficiencies: a) Most estimation models are statistical analysis models or off-line supervised learning models which can't be applied for practical applications. b) Most models just use single classifier, but the information about single classifier alone is always insufficient to get the best result. c) As most studies pointed out, the changing patterns are different in different fatigue states. But most of the existing methods haven't taken this knowledge into consideration. d) Fatigue transition is a dynamic process but we are still using the EEG temporal static features, the dynamic information is wasted.

To deal with the first problem, we introduce linear dynamic system (LDS) technique [11,9]. LDS combines both the spatial and temporal information of EEG features and keeps time series information when smoothing features in second-scale [10]. For the second and third problems, we adopt the parallel hidden Markov models (PHMM). HMMs have been applied in many fields including speech recognition, activity recognition and motor imagery, but there is few research using HMMs to classify fatigue [4]. As we know, HMMs are capable of differentiating different signals that their statistical properties changing over time, thus considering different fatigue state have different changing patterns, we construct corresponding Hidden Markov models to imitate the way of different fatigue states transition. In addition, we use fuzzy integral as a pattern classifier combination strategy in a more reasonable way [3]. For the fourth problem, the EEG temporal dynamic features are used to classify different EEG patterns.

This paper is organized as follows. In Sect 2, the proposed method and the main processes including data processing, dynamic feature extraction and classification scheme are described. In Sect 3 we introduce the experimental setup and the collected data forms. The experimental results and discussions are reported in Sect 4, followed by conclusions in Sect 5.

2 Methods

The overall flow chart of the proposed fatigue classification method is depicted in Fig 1. The original EEG signals and subject's performance are the inputs from the most left and the optimal solution from the right bottom is the output. From original EEG, we can extract the static and dynamic features. From subject's performance we can get the reference fatigue level. All the processes will be presented in this section.

2.1 Data Processing

We use the error rate of subject's reaction as the reference. This is based on the viewpoint that high fatigue level means making more mistakes. By averaging the error rate within a 2-minute window at 2-second step, the reference fatigue level is obtained.

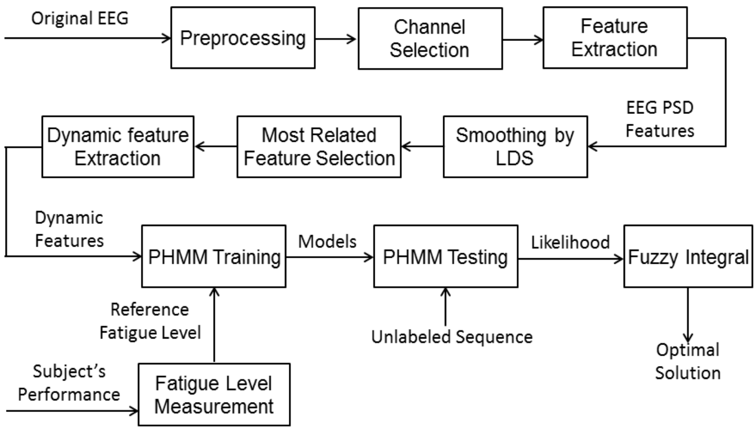

Fig. 1. Flow chart of the proposed EEG-based fatigue classification method

Since raw EEG signals contain much noise, we need to wipe off the EEG-unrelated signals and fatigue-unrelated signals, and remain the highly fatigue-related EEG signals.

In the preprocessing process, we discard the first few minutes EEG signals because subjects need to adapt the experiment in the very beginning. Then we remove the artifacts and use a band-pass filter (1Hz-16Hz) to remove the low-frequency and high-frequency noise. In the channel selection process, we select 6 EEG channels (P1, Pz, P2, Po3, Poz, Po4) from the posterior scalp which are proved to be the most fatigue-related region in our previous work [10]. In the feature extraction process, we use short-time Fourier transform (STFT) with a 2 seconds Hamming window and 0.5 seconds overlapping to calculate the log power spectral density of every single frequency in 1Hz-16Hz. Next we use a linear dynamic system (LDS) approach to smooth the features, because LDS-based filter has higher time resolution and ability to keep the spatial and temporal information in EEG signal smoothing. In the feature selection process, we use the correlation coefficients between features and reference fatigue level (the reference fatigue level is still continuous here) to measure the importance of features. We select the top Q high-correlation-coefficient features in training data, and select corresponding features in testing data.

2.2 Dynamic Feature Extraction

The dynamic features are calculated using the following first-order orthogonal polynomial formula [4,2]:

$$\Delta F(l) = \frac{\sum_{i=-K}^{K} iF(l-i)}{\sum_{i=-K}^{K} i^2}, K+1 \leq l \leq N-K \tag{1}$$

where $F(l)$ is the static feature, l is the sample index, N is the size of the sample set, K is the window length, which should be carefully chosen to balance the weights of the adjacent samples, and $\Delta F(l)$ is the dynamic feature of input $F(l)$. When $F(l)$ is static feature, $\Delta F(l)$ will be the first-order dynamic feature. While $F(l)$ is first-order dynamic feature, $\Delta F(l)$ will be the second-order dynamic feature.

Each static feature and its corresponding dynamic features are combined to form one feature vector. So the number of static features is equal to the number of feature vectors. All feature vectors will be processed independently later.

2.3 Classification Scheme

The flow chart of the classification scheme proposed in this paper is shown in Fig. 2, which is an example for 2 classes, Q is the number of feature vectors.

Before training PHMMs, the samples should be partitioned into fixed-length sequences. Then, the continuous reference fatigue level should turn into discrete value refer to different classes. Ranges of each class can be divided equally, or divided by artificial thresholds.

Suppose we have M classes and Q feature vectors. After training process, we get $M * Q$ HMMs. All sequences of each class and each feature vector will be used to train a HMM with mixture of Gaussians outputs. The fatigue is continuous varying, so the states of HMM can only transfer to their adjacent states and themselves. The state transition diagram with three states applied in our method is shown in Fig. 3.

The HMM parameters are initialized with k-means algorithm, and using the Baum-Welch algorithm in training [8,4]. When we have a new unlabeled sequence, we compute the likelihood of each HMMs based on the new sequence

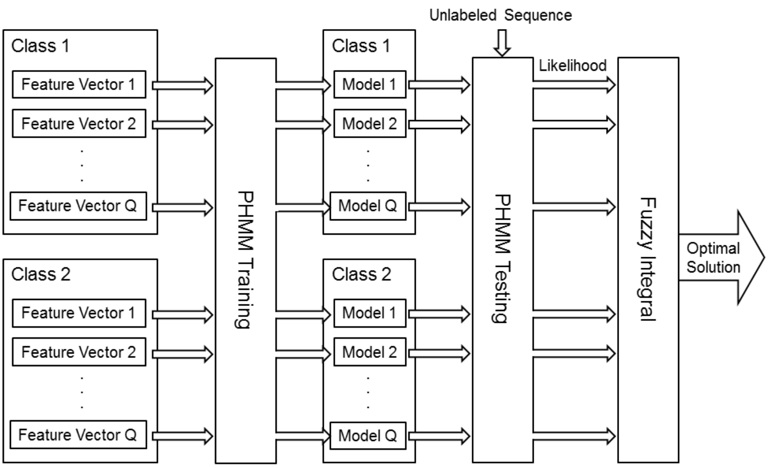

Fig. 2. Flow chart of the proposed classification scheme

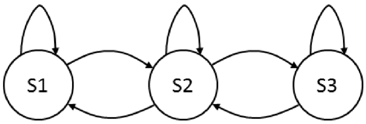

Fig. 3. The state transition diagram of our HMM with three states

in the testing process. Then we use fuzzy integral algorithm to determine which class is the optimal solution.

We can also use some simple pattern classifier combination strategies like maximal, sum, voting and product rule. All the definitions can be found in [5]. Compared with fuzzy integral, these methods need no training process. However, they are more inaccuracy. We have implemented all these methods and the results will be shown in Sect 4.

3 Materials

There is no fatigue EEG database available online till now. So we use the database collected in our laboratory. The following sections present the experiment settings and the data forms.

3.1 Experiment

In our experiment, subjects need to complete a monotonous visual task in which subjects are asked to recognize the sign color and press the correct button on the response pad.

There are four colors in all, each has more than 40 different traffic signs. The NeuroScan Stim2 software presents 5$\sim$7 seconds black screen and 0.5 seconds random sign in each trial. The experiment room is soundproof and normal illuminated. Subjects sit in a comfortable chair, 2 feets away from LCD. In order to collect sufficient and useful data, the experiment starts from about half hour after lunch, lasting more than one hour, better if including the whole process from wakefulness to sleep. Totally 9 subjects aging from 19 to 28 years old have participated in our experiment, each subject at least twice.

3.2 Data Collection

There are two kinds of collected data. One is the EEG signal. A total of 62 channels EEG signals sampled with 500Hz are recorded by the NeuroScan system. The system will primarily filter the EEG signals between 0.1 and 100Hz to remove some high-frequency noise from surroundings and muscles. The electrodes are arranged based on extended 10/20 system. The reference electrode is located on the top of the scalp.

The other is the visual stimulus sequence and subjects' performance. According to these data, we can estimate subjects' reference fatigue level during experiment, which helps us training and evaluating our approach.

4 Results and Discussions

EEG signal is time sequence, so we can't randomly select training and testing data in one session. So we use two sessions of one subject to train and test separately. There are totally 18 pairs of training and testing sessions.

Table 1. The RMSE for different class numbers and different features

No. of class	static	1st order	2nd order
2	6.84 ± 0.03	6.54 ± 0.02	$\mathbf{6.06 \pm 0.04}$
3	11.31 ± 0.08	11.25 ± 0.02	$\mathbf{11.15 \pm 0.10}$
4	18.05 ± 0.14	17.84 ± 0.08	$\mathbf{16.91 \pm 0.15}$
5	23.64 ± 0.04	23.62 ± 0.04	$\mathbf{22.54 \pm 0.07}$

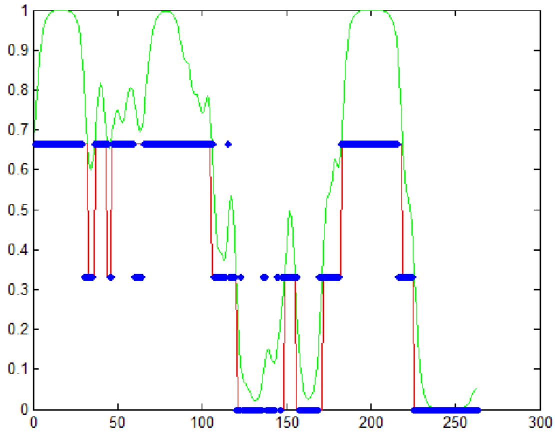

Fig. 4. Example of one testing result with 3 classes

In Table 1, we calculate the root mean squared error (RMSE) of all 18 testing error rates with different features and different class numbers. Fatigue is generally divided into 5 periods, so we choose 2 to 5 classes in our test. The second column to the fourth column refer to different features. The pattern classifier combination method is fuzzy integral and the classifier's parameters are tuned by trial and error. The best results are highlighted in bold.

We can see that, firstly, the RMSE increases quickly with the number of classes increasing. Because when the number of classes increases, the range of each class will be narrower, so the confused boundary will greatly affect the classification accuracy on adjacent classes. Secondly, the dynamic features perform better than static features, and 2nd order outperforms 1st order. This means the dynamic information contributes to classify fatigue levels.

Figure 4 shows a testing result with 3 classes, 5 Gausses, and 3 fatigue states. And the classifier combination method is fuzzy integral. The horizontal axis means sequence index. The vertical axis means the fatigue level value (lower value is lower fatigue). The green line is the continuous fatigue level value. The red line is the discrete fatigue level value, which is equally divided and valued as 0, 1/3 and 2/3. The blue points is the estimated discrete fatigue level value.

In Fig. 4, there are two main kinds of error points. One is at the junction of two adjacent classes with a bias towards the previous class. The other is at the fluctuate of continuous fatigue level with a bias towards the fluctuate direction.

Table 2. The RMSE for different class numbers and different classifier combination methods

No. of class	sum	voting	product	maximal	fuzzy integral
2	6.38 ± 0.06	6.17 ± 0.05	6.11 ± 0.07	7.44 ± 0.14	$\mathbf{6.06 \pm 0.04}$
3	11.80 ± 0.10	12.53 ± 0.04	11.53 ± 0.10	14.32 ± 0.15	$\mathbf{11.15 \pm 0.10}$
4	17.93 ± 0.13	18.37 ± 0.11	17.60 ± 0.03	19.31 ± 0.15	$\mathbf{16.91 \pm 0.15}$
5	23.93 ± 0.01	25.36 ± 0.15	22.82 ± 0.01	27.82 ± 0.22	$\mathbf{22.54 \pm 0.07}$

Next, we replace fuzzy integral with different classifier combination methods and compare their performance. The result is presented in Table 2. We can see that, the fuzzy integral method outperforms other methods. That means by using fuzzy integral the results of different classifiers are combined more reasonably. The maximal method performs worst, cause this method emphasizes the maximal value and undervalues the general results of all classifiers.

Table 3. The RMSE for different class numbers and different classification methods

No. of class	PHMM	SVM
2	$\mathbf{6.06 \pm 0.04}$	8.22 ± 0.05
3	$\mathbf{11.15 \pm 0.10}$	16.45 ± 0.07
4	$\mathbf{16.91 \pm 0.15}$	23.55 ± 0.12
5	$\mathbf{22.54 \pm 0.07}$	28.38 ± 0.09

Last, we compare PHMM with SVM. LibSVM is used to train and test models [1]. Here we replace the PHMM modules in Fig. 2 by the SVM methods, in which RBF kernel function is used and the optimal parameters are selected by Cross Validation. The classifier combination method is still fuzzy integral. The result is shown in Table 3. Obviously our method performs better than SVMs. Because PHMM can construct the internal transition regularity of different fatigue states. And SVMs only use the information of feature space.

5 Conclusions

This paper presents a novel EEG-based fatigue classification method by integrating PHMM and fuzzy integral. In this method, we introduce dynamic features to our feature extraction process. And the dynamic features are proved to be better than static features by our experimental results. In the classification scheme, we use PHMM to construct the changing patterns of different fatigue states and use fuzzy integral to combine the results of different classifiers. By comparison, PHMM outperforms SVMs, and the results show changing information is discriminative in EEG-based fatigue classification. We also evaluate the performance of different classifier combination methods (fuzzy integral, maximal, sum, product and voting). The results show that fuzzy integral outperforms others.

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References

1. Chang, C.C., Lin, C.J.: LIBSVM: A library for support vector machines. ACM Transactions on Intelligent Systems and Technology 2, 27:1–27:27 (2011), software, `http://www.csie.ntu.edu.tw/~cjlin/libsvm`
2. Deller, J., Proakis, J., Hansen, J.: Discrete-time processing of speech signals. Macmillan (2000)
3. Grabisch, M.: Fuzzy integral for classification and feature extraction. Fuzzy Measures and Integrals - Theory and Applications, 415–434 (2000)
4. Lederman, D., Tabrikian, J.: Classification of multichannel eeg patterns using parallel hidden markov models. Medical and Biological Engineering and Computing, 1–10 (2012)
5. Li, B., Lian, X., Lu, B.: Gender classification by combining clothing, hair and facial component classifiers. Neurocomputing, 18–27 (2011)
6. Molloy, R., Parasuraman, R.: Monitoring an automated system for a single failure: Vigilance and task complexity effects. Human Factors: The Journal of the Human Factors and Ergonomics Society 38(2), 311–322 (1996)
7. Oken, B., Salinsky, M., Elsas, S.: Vigilance, alertness, or sustained attention: physiological basis and measurement. Clinical Neurophysiology 117(9), 1885–1901 (2006)
8. Rabiner, L.: A tutorial on hidden markov models and selected applications in speech recognition. Proceedings of the IEEE 77(2), 257–286 (1989)
9. Shi, L., Lu, B.: Dynamic clustering for vigilance analysis based on eeg. In: Proc. of 32nd International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 54–57 (2008)
10. Shi, L., Lu, B.: Off-line and on-line vigilance estimation based on linear dynamical system and manifold learning. In: Proc. of 32nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 6587–6590 (2010)
11. Shi, L., Yu, H., Lu, B.: Semi-supervised clustering for vigilance analysis based on eeg. In: Proc. of 20th IEEE International Joint Conference on Neural Networks, pp. 1518–1523 (2007)
12. Weinger, M.: Vigilance, boredom, and sleepiness. Journal of Clinical Monitoring and Computing 15(7), 549–552 (1999)