Estimating Vigilance in Driving Simulation using Probabilistic PCA

Mu Li, Jia-Wei Fu and Bao-Liang Lu* *Senior Member, IEEE*

***Abstract*— In avoiding fatal consequences in accidents behind steering wheel caused by low level vigilance, EEG has shown bright prospects. In this paper, we propose a novel method for discriminating two different vigilance states of the subjects, namely wake state and sleep state, during driving a car in a simulation environment. After filtering the EEG data into a specific frequency band, we use probabilistic principle component analysis (PPCA) to reduce the data dimension. Then we modal each vigilance state as a lower dimension Gaussian random variable by applying PPCA again. The feature related to class posterior probability is calculated for classification. The experimental results show satisfying time resolution ($\leq$ 5s) and high accuracy ($\geq$ 96%) across five subjects on common frequency bands β (19-26Hz), γ (38-42Hz), and broad band (8-30Hz).**

I. Introduction

Retaining vigilance above a constant level is of vital importance to car, airplane or plant operators, but it is difficult to achieve this goal, especially while performing repetitive, monotonous and long-term tasks. Previous studies have shown that low vigilance due to drowsiness is a major factor to automobile crashes [1]. Thus to develop accurate and non-intrusive real-time techniques to estimate vigilance is highly desirable in a variety of human-machine interaction systems.

During the past few decades, many studies have shown that information related to vigilance can be found in EEG [2]. Comparing to other physical and physiological signals such as facial expression and skin potential [3], EEG can directly represent human brain electronic activity and has higher time resolution. Some changes in EEG spectrum have been observed while the vigilance state varies [4][5]. These include decreased β activity and increased α activity with decreased vigilance. However, previous results have also shown that there are a variability of key parameters denoting vigilance across different subjects [6].

Most previous studies have focused on applying supervised learning methods to estimate vigilance states [7]. But this requires a standard criterion for vigilance scale labeling, while the existing labeling methods are complex, expensive and unreliable. Some researchers defined the vigilance as several discrete stages to simplify the outputs [8]. This caused fluctuating prediction results on minute scale, and the shorter time window, the more fluctuations can be observed. Lin and colleagues made use of the deviation between the center of vehicle and the cruising lane to measure the alertness level indirectly [9][10]. This made it possible to quantify subject's vigilance continuously during driving task rather than discretely defining several stages. As a result, a close relationship between minute-scale changes in driving performance and the EEG power spectrum was demonstrated [11]. Another direction is to use unsupervised learning method to help labeling data [12].

The scope of our study is mainly to classification two different vigilance states, namely the sleep state and wake state, during the driving simulation experiment. We assume that low dimension latent Gaussian random variables for the high dimension EEG signals, then use maximum likelihood to estimate the model parameters. The features related to class posterior probabilities are used for classification. Different EEG frequency bands and time resolutions are considered in this study.

This paper is organized as follows. In section II, our experiment setup of driving simulation is introduced. The proposed EEG feature extraction method is presented in section III. Experimental results are described in section IV. Finally, the conclusions and future work are given in section V.

II. Methods

A. Experiment Setup

In the experiment, each subject was required to drive a car in a driving simulation environment as illustrated in Fig. 1. The subjects sat on a chair and drove with a steering wheel. The simulating driving scenes are displayed on a 19' LCD screen with 70cm length in front of him/her. The experiment map consists of two long straight roads around 10km and two spin turns. At the speed of 60 km/h, it takes about 10mins to finish one round. The sceneries are monotonous so the subject may feel drowsy easily and even fall asleep. The experiment was carried on in an illuminated and sound proof room, and lasted one and half an hour. The temperature of the room was about 27 degrees and the humidity was between 40% and 60%.

B. Subjects

Ten healthy young volunteers, aged 18-28 years old, participated in this driving simulation experiment. The subjects were informed that the purpose of this experiment was to investigate EEG patterns in different vigilance levels, and were required to abstain from alcohol and caffeine one day before the experiment. At the beginning of the experiment,

Asterisk indicates corresponding author. This work was supported in part by the National Natural Science Foundation of China under the grants NSFC 60473040 and NSFC 60773090, the Microsoft Laboratory for Intelligent Computing and Intelligent Systems of Shanghai Jiao Tong University, and the Okawa Foundation Research Grant. M. Li, J. Fu, and B. L. Lu are with the Department of Computer Science and Engineering, Shanghai Jiao Tong University, Shanghai 200240, China (email: {mai_lm, gawafu, bllu}@sjtu.edu.cn)

Preprint submitted to 30th Annual International IEEE EMBS Conference.
Received April 7, 2008.

Fig. 1. Driving simulation environment. Here EEG signals are captured from scalp by the electrode cap (1), the subject's face expression is recorded by a DV (2), and driving scenes are displayed on the LCD screen (3).

there was a 10 minutes practice to help the subject get used to the environment. The EEG data from five subjects, who had shown a tendency to fall asleep during the driving simulation, were selected for data analysis in this paper.

C. Data Acquisition

The subjects were fitted with a 62-channel electrode cap during the experiment. The Ag/AgCl electrodes are mounted inside the cap with bipolar references at papillary place behind ears. The electrodes were arranged according to the international 10-20 system. The contact impedance between electrodes and skin was kept less than 50kΩ. The EEG data were recorded with 32-bit quantization level at a sampling rate of 1000Hz. The subject's facial expression and the driving screen during the whole experiment were recorded by two DV cameras, which were used for labeling the EEG data.

D. Data Labeling

We labeled two time segments, namely the sleep segment and wake segment, for each experiment according to the videos. The wake segment was usually chosen as the several minutes at the beginning of the experiment, when the subject was clear-headed with eyes open and driving well. While the sleep segment was usually chosen in the middle, on which the subject closed his/her eyes and had stopped driving.

E. Data Processing

The flowchart of EEG signal processing procedure is depicted in Fig. 2. The training process consists of three steps. In the first step, the raw EEG data, which is a channel-by-time matrix, is filtered into frequency bands using finite impulse response (FIR) filter. Based on the consideration of possible inter-subject differences, we try six different frequency bands, which are α (8-12Hz), lower α (8-10Hz), upper α (10-12Hz), β (19-26Hz), γ (38-42Hz) and broad band (8-30Hz) [13]. Since spectrum information below 8Hz is ignored here, removing artifacts such as EOG and EMG is not necessary, and the experimental results show that EOG or EMG affects the classification accuracy little.

In the second step, the filtered data is reduced into D dimension by applying probabilistic principle component analysis (PPCA), which results in a D-by-T matrix. In the third step, assuming an M-dimension latent Gaussian random variable for each class, the model parameters are estimated by using PPCA, .

The testing process also consists of three steps. The first two steps are the same as the training process. In the third step, the features f_1 and f_2 are calculated by the model parameters obtained from the training process, which are proportional to the logical class posterior probabilities. The details of feature extraction algorithm are to be stated in Section III.

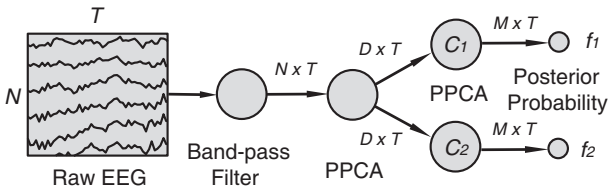

Fig. 2. The flowchart of EEG data processing.

III. EEG Feature Extraction

Given an N-channel spatial EEG signal $\mathbf{x}$ at time t, which is an N-by-1 vector, we assume $\mathbf{x}$ an N-dimensional Gaussian random variable with dimension D. Let $\mathbf{z}$ be the latent variable with a zero-mean unit-covariance Gaussian distribution $p(\mathbf{z}) = \mathcal{N}(\mathbf{z}|0, \mathbf{I})$, the conditional distribution of $\mathbf{x}$ conditioned on $\mathbf{z}$, which is also a Guassian, has the form

$$p(\mathbf{x}|\mathbf{z}) = \mathcal{N}(\mathbf{x}|\mathbf{W}\mathbf{z} + \boldsymbol{\mu}, \sigma^2\mathbf{I}), \tag{1}$$

where $\mathbf{W}$ is an $N \times D$ linear transformation matrix, and $\boldsymbol{\mu}$ and σ^2 governs the mean and variance of $\mathbf{x}$. The marginal distribution of $\mathbf{x}$ is given by

$$p(\mathbf{x}) = \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \mathbf{W}\mathbf{W}^{\mathrm{T}} + \sigma^2\mathbf{I}). \tag{2}$$

The parameters of this model are obtained by using maximum likelihood, called probabilistic principle component analysis [14].

Assume that we have T signals, denote by $\mathbf{X} = \{\mathbf{x}_t\}_{t=1}^T$, with mean $\overline{\mathbf{x}}$ and covariance $\mathbf{S}$ given by

$$\overline{\mathbf{x}} = \frac{1}{T}\sum_{t=1}^{T}\mathbf{x}_t, \ \mathbf{S} = \frac{1}{T}\sum_{t=1}^{T}(\mathbf{x}_t - \overline{\mathbf{x}})(\mathbf{x}_t - \overline{\mathbf{x}})^{\mathrm{T}}. \tag{3}$$

The log likelihood function corresponding to (2) is

$$\ln p(\mathbf{X}|\boldsymbol{\mu}, \mathbf{W}, \sigma^2) = \sum_{t=1}^{T}\ln \mathcal{N}(\mathbf{x}_t|\boldsymbol{\mu}, \mathbf{W}\mathbf{W}^{\mathrm{T}} + \sigma^2\mathbf{I}). \tag{4}$$

By setting the derivative of (4) with respect to $\boldsymbol{\mu}$, $\mathbf{W}$, and σ^2 to zero, respectively, we have

$$\boldsymbol{\mu}_{\mathrm{ML}} = \overline{\mathbf{x}} \tag{5}$$

$$\mathbf{W}_{\mathrm{ML}} = \mathbf{U}_D(\mathbf{L}_D - \sigma^2\mathbf{I})^{1/2} \tag{6}$$

$$\sigma^2_{\mathrm{ML}} = \frac{1}{N-D}\sum_{i=D+1}^{N}\lambda_i, \tag{7}$$

where $(\lambda_1, \cdots, \lambda_N)$ is the eigenvalues of the covariance matrix $\mathbf{S}$ with descending order, L_D is the diagonal matrix

Preprint submitted to 30th Annual International IEEE EMBS Conference.
Received April 7, 2008.

diag$(\lambda_1, \cdots, \lambda_D)$, and $\mathbf{U}_{\text{ML}}$ is a $N \times D$ matrix whose columns are eigenvecters of $\mathbf{S}$ correspoding to $\mathbf{L}_D$.

Now we define a transformation P

$$P(\mathbf{x}) = \mathbf{L}_{\text{ML}}^{-1/2}\mathbf{W}_{\text{ML}}^{\dagger}(\mathbf{x} - \boldsymbol{\mu}_{\text{ML}}) \tag{8}$$

which transfers $\mathbf{x}$ into a zero-mean and unit-covariance D-dimensional Gaussian random variable. Here the symbal † denotes pseudoinverse.

Further, assume that $\mathbf{x}$ consists of two different kinds of EEG signal $\mathcal{C}_1$ and $\mathcal{C}_2$, namely sleep and wake. Let $\mathbf{X}^{(i)} = \{\mathbf{x}|\mathbf{x} \in \mathcal{C}_i\}$, and $\mathbf{B}^{(i)}$ be the corresponding trasformed signals, i.e. $\mathbf{B}^{(i)} = P(\mathbf{X}^{(i)})$, for $i = 1, 2$. By defining the covariance matrix $\mathbf{S}^{(i)}$ of $\mathbf{B}^{(i)}$ as (3), we could get $\mathbf{S}^{(1)} + \mathbf{S}^{(2)} = \mathbf{I}_D$ [15][16]. Assuming an M-dimensional latent Gaussian random variable $\mathbf{r}$ for $\mathcal{C}_1$ and $\mathcal{C}_2$, we get the conditional distribution of transformed signal $\mathbf{b}$ by

$$p(\mathbf{b}|\mathbf{r}) = \mathcal{N}(\mathbf{b}|\mathbf{W}^{(i)}\mathbf{r} + \boldsymbol{\mu}^{(i)}, \sigma^{(i)2}), \tag{9}$$

for $\mathbf{b}$ in $\mathbf{B}^{(i)}, i = 1, 2$. Applying PPCA again, the marginal distribution is given by $p(\mathbf{b}) = \mathcal{N}(\mathbf{b}|\mathbf{0}, \boldsymbol{\Sigma}_{\text{ML}}^{(i)})$ with

$$\boldsymbol{\Sigma}_{\text{ML}}^{(i)} = \mathbf{U}_M^{(i)}(\mathbf{L}_M^{(i)} - \sigma_{\text{ML}}^{(i)})\mathbf{U}_M^{(i)\text{T}} + \sigma_{\text{ML}}^{(i)2}\mathbf{I}_M, \tag{10}$$

where the parameters $\mathbf{U}_M^{(i)}$, $\mathbf{L}_M^{(i)}$, and $\sigma_{\text{ML}}^{(i)2}$ are similarly defined as before.

In order to classify a new coming trial $\mathbf{X}^{\text{new}}$, which is an $N \times T'$ matrix, into class $\mathcal{C}_1$ or $\mathcal{C}_2$, we first transform $\mathbf{X}^{\text{new}}$ into $\mathbf{B}^{\text{new}}$ using transformation P, then we consider the feature f_i for $i = 1, 2$

$$\begin{aligned} f_i &= \sum_{t=1}^{T'} \mathcal{N}(\mathbf{b}_t|\mathbf{0}, \boldsymbol{\Sigma}_{\text{ML}}^{(i)}) \\ &= \ln p(\mathbf{B}^{\text{new}}|\mathcal{C}_i) \propto \ln p(\mathcal{C}_i|\mathbf{B}^{\text{new}}), \end{aligned} \tag{11}$$

where we assume the prior probability $p(\mathcal{C}_i)$ and $p(\mathbf{B}^{\text{new}})$ to be constant and conditional independent on $\mathcal{C}_i$, then f_i is proportional to the logical class posterior probability $p(\mathcal{C}_i|\mathbf{B}^{\text{new}})$.

The time complexity of the proposed method is linear with the number of samples. The first time using PPCA costs $\mathcal{O}(N^2 \times D \times T)$ time, and the second time costs $\mathcal{O}(D^2 \times M \times T)$. Since the parameters N, D, and M are very small comparing to the number of samples T, the time complexity is $\mathcal{O}(T)$.

IV. Results

For the five chosen subjects, we selecte around 10 minutes sleep data and equal length wake data for each one, and then we divide the data into ten segments for cross-validation. Seven segments are selected for training and the remainder three segments for testing, we repeat that for ten times to get average accuracy. Let the classes $\mathcal{C}_1$ and $\mathcal{C}_2$ be wake and sleep, respectively. In the training stage, we choose the number of dimension D which captures 90% eigenvalues for the first time of applying PPCA, and then we use a fixed dimension $M = 3$ for the second time of using PPCA. In the testing stage, we use 5s length trials with 2.5s overlap between two adjacent trials. A trial is classified into wake ($\mathcal{C}_1$) if the corresponding feature f_1 is larger than f_2 or sleep ($\mathcal{C}_2$) otherwise.

TABLE I

The test accuracies (%) of five subjects. The lengthes of awake and sleep segments are given in length column with format awake/sleep in minute. Date are filtered into six common considered frequency bands.

Sub.	Length	α	Lα	Uα	β	γ	8-30Hz
1	13 / 13	89.6	82.9	93.2	98.2	94.1	98.8
2	6 / 6	84.0	91.3	85.3	100.0	100.0	96.8
3	11 / 11	96.9	87.6	95.9	98.4	98.5	96.1
4	13 / 13	88.1	88.9	86.3	98.1	98.1	95.7
5	10 / 10	93.8	91.1	96.7	89.1	98.4	96.2

The test accuracies for five subjects are shown in Table I. Six commonly used frequency bands are considered, which are α, lower α, high α, β, γ, and a broad band, corresponding to 8-12Hz, 8-10Hz, 10-12Hz, 19-26Hz, 38-42Hz and 38-42Hz, respectively. The best result for each subject is higher than 98% (100% for subject 2 and 98% for subject 1, 3, 4 and 5, respectively), which is obtained with different frequency bands. Notice that β, γ, and 8-30Hz give average subjects accuracies 97%, 98% and 97%, respectively. Further, γ and 8-30Hz are stable across subjects.

The test accuracy as a function of trial length for each subject is illustrated in Fig. 3, in which the trial length changes from 10s to 0.4s and the frequency band is 8-30 Hz. As we expected, the accuracy declines as the trial length shortens. But notice that the accuracy changes little with trial length varies from 10s to 5s, and it is still acceptable for 1s, with 96%, 95%, 96%, 94% and 92% for subject 1, 2, 3, 4 and 5, respectively.

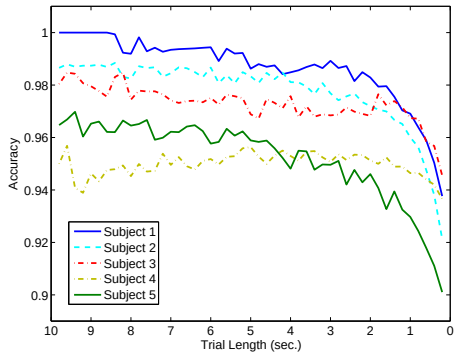

Fig. 3. Accuracy v.s. trial length. The accuracy delines slowly with trial length shortening, and is acceptable for 1 sec. trial length.

We present the performance of subject 3 during the whole experiment in Fig.4. Two feature estimation methods are used, one is comparing f_1 and f_2 and classify the trial into classes wake or sleep as before, the other is the normalization of features $f_1/(f_1 + f_2)$, we call it $\mathcal{C}_1$ score, which is an approximation of the class posterior probability.

The recorded face video shows that subject 3 is awake

Preprint submitted to 30th Annual International IEEE EMBS Conference.
Received April 7, 2008.

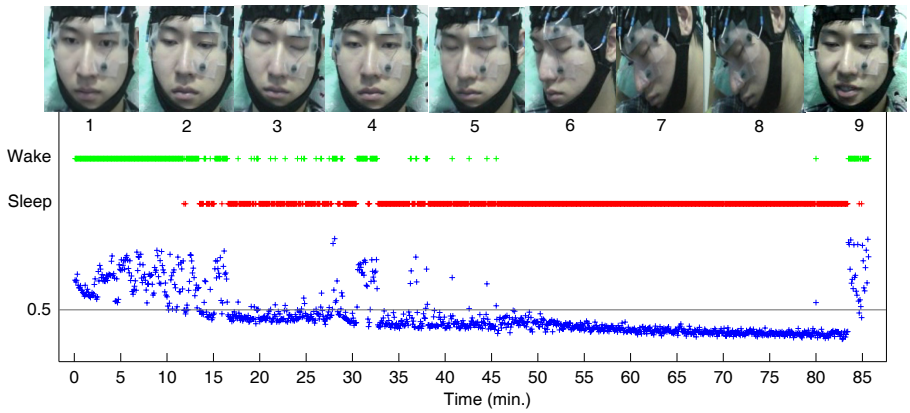

Fig. 4. The performance of subject 3 during an 86-min length driving simulation experiment. X-axis is the time in minute. Nine face video snippets are presented in the top, whose times are corresponding to the x-position of the numbers below them. The classification results are given in the WAKE and SLEEP rows; each plus sign means a 5 sec. time. The weighted mean of feature f_1 and f_2, i.e. $f_1/(f_1+f_2)$, are showed in the bottom. The 0.5 threshold line is also drawn.

at the beginning 10mins (according to snippet 1 in Fig. 4) and the last 3mins (snippet 9), is drowsy from 10mins to 45mins (snippet 2-5) and fall asleep from 45mins to 83mins (snippet 6-8). The training data for wake we choose is the first 10mins, and the time segment from 45mins to 55mins for sleep. From Fig. 4, notice that two wake segments at the beginning and end are classified correctly, and a temporary arousal around 30mins is also recognized. During the drowsy segment (from 10mins to 45 mins), the classification results are fluctuating to some extent. Further, the $\mathcal{C}_1$ score shows a continuous variety with the time, especially it declines smoothly as the sleep deepens (from 50mins to 80mins).

V. Conclusions and Future Work

In this paper, we have presented an EEG signal classification method for distinguishing wake and sleep states on driving simulation experiment, which using probabilistic principle component analysis to reduce the dimension and then using probabilistic principle component analysis again for each state to get the posterior probability feature. Our method gives over 96% average accuracy with 5s time resolution for five subjects on three different frequency bands, which are β (19-26 Hz), γ (38-42 Hz), and broad band (8-30 Hz), respectively. The accuracy is still acceptable even with 1s time resolution.

Our method can be used as a real time classifier directly. After training using about 20 minutes length data, it can output high accuracy for high time resolution (less than 5s). From Fig. 4, the $\mathcal{C}_1$ score varies continuously with the time in a certain extent continuous, we are seeking real-time continuous vigilance estimation method.

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Preprint submitted to 30th Annual International IEEE EMBS Conference.
Received April 7, 2008.