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Multivariate autoregressive models and kernel learning algorithms for classifying driving mental fatigue based on electroencephalographic

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ABSTRACT

Long-term driving is a significant cause of fatigue-related accidents. Driving mental fatigue has major implications for transportation system safety. Monitoring physiological signal while driving can provide the possibility to detect the mental fatigue and give the necessary warning. In this paper an EEG-based fatigue countermeasure algorithm is presented to classify the driving mental fatigue. The features of multichannel electroencephalographic (EEG) signals of frontal, central and occipital are extracted by multivariate autoregressive (MVAR) model. Then kernel principal component analysis (KPCA) and support vector machines (SVM) are employed to identify three-class EEG-based driving mental fatigue. The results show that KPCA–SVM method is able to effectively reduce the dimensionality of the feature vectors, speed up the convergence in the training of SVM and achieve higher recognition accuracy (81.64%) of three driving mental fatigue states in 10 subjects. The KPCA–SVM method could be a potential tool for classification of driving mental fatigue.

1. Introduction

Mental fatigue is a gradual and cumulative process and is thought to be associated with a disinclination for any effort, reduced efficiency and alertness and impaired mental performance. The major symptoms of mental fatigue is a general sensation of weariness, feeling of inhibition and impaired activity. Driving mental fatigue is widely recognized as a core safety issue in the transportation. This is four times more likely to be a contributor to workplace impairment than drugs or alcohol. Driving mental fatigue-related road accidents alone cost around Australian $ 3 billion per year and become a substantial financial burden on the community (The Parliament of the Commonwealth of Australia, 2000). Developing and establishing an accurate and non-invasive real-time system for monitoring driver's mental fatigue is quite important to reduce road accidents and lower social cost in traffic safety.

As a result, numerous field studies and laboratory experiments were conducted to produce the real-time and non-obtrusive means for detecting driving mental fatigue. Among these different driving mental fatigue detection methods, there are two main fields with techniques based on physiological phenomena achieving higher detection accuracy. One approach focuses on driver and vehicle physical changes such as the inclination of the driver's head, sagging posture, and decline in gripping force on steering wheel or the open/close state of the eyes or steering angle, vehicle lateral position, vehicle speed and vehicle yaw rates (Hu & Zheng, 2009; Lal, Craig, Boord, Kirkup, & Nguyen, 2003; Sayed & Eskandarian, 2001; Smith, Shan, & da Vitoria Lobo, 2000). But these methods are limited to depending on the vehicle type and driving conditions. 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 mental fatigue state. While numerous physiological indicators were available to measure mental fatigue, the EEG is widely regarded as the physiological "gold standard" for the assessment of mental fatigue (Bouchner, 2006; Lal & Craig, 2001; Lin et al., 2005; Jap, Lal, Fischer, & Bekiaris, 2008). EEG signals contain a lot of information of the cognitive states such as alertness and arousal and they have plentiful information related to the different physiological states of the brain and can be a very effective medium for understanding the complex dynamical behavior of the brain.

Mental fatigue is a complex phenomena which is relative to nerve-central activity. One must look at activity distributed over the entire scalp in order to detect brain state during mental fatigue. Thus, multichannel EEG must be recorded because single-channel

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brainwaves do not provide enough information (Anderson, Stolz, & Shamsunder, 1998; Franaszczuk, Blinowska, & Kowalczyk, 1985).

In this study, a multivariate autoregressive (MVAR) model is applied to extract EEG features for measuring driving mental fatigue. A newly-developed machine-learning technique – support vector machine (SVM) combined kernel principal component analysis (KPCA) is adopted to differentiate three driving mental fatigue states.

2. Materials and methods

2.1. Subjects

To reduce inter-subject differences, 13 male graduate students (mean age, 23.8 years; range 22–26 years) were recruited from students of Xi'an JiaoTong University to perform the experiments. All participants provided informed consent prior to participating in the study. All subjects did not have any actual driving experience and none of them was able to operate the stick shift car. They were familiar with operating a computer and had the experience of playing video game. All subjects were trained before the experiment until they performed the simulative driving system expertly. None of them worked night shifts or used prescription medication and medical contraindications such as severe concomitant disease, alcoholism, drug abuse, and psychological or intellectual problems likely to limit compliance. According to their self-reports, all subjects had normal or corrected-to-normal vision and were right-hand dominated.

2.2. Apparatus

The driver simulator equipment consisted of a car frame with an in-built steering wheel, gas and brake pedals, clutch, manual shift and a horn and turn signal. The visual display of the (virtual reality) VR-based driving simulative environment is a 19 inch Liquid Crystal Display at a distance of 80 cm from the subject's eyes. The LCD shows the road environment, the current speed and other road stimuli. The system also can provide engine noise and nearby traffic noise. The simulative route and traffic sign are standardized with national traffic law.

2.3. Experiment design

Previous literatures pointed out that driving mental fatigue occurred in a monotonous driving environment. Thus, a highway scene was selected in our experiment. Furthermore, we designed the simulative driving track with the following requirements: The route was simple so that the drivers could perform as easily as possible; There were few scenery changes and no moving objects in the three-lane road with no inclination to reduce outside stimuli; A very light curvature was chosen so that drivers should pay their attention to steering all the time. One lap would take about 7 min when the subjects kept the car speed at about 100 km/h. Each driving experiment lasted about 150 min continuously.

This study had the institute's Human Research Ethics Committee approval, and was conducted in a dimly lit, sound-attenuated, electrically shielded and temperature-controlled laboratory. Training was carried out previously. Participants were asked to sleep adequately the day before the study, refrain from consuming alcohol caffeine, tea or food as well as smoking approximately 12 h before the study, and reported compliance with these instructions. To avoid the influence of circadian fluctuations on subjects, the experiments were conducted approximately at 8:00 AM or 2:30 PM during the normal work-time. Before the experiment, the subjects learned the whole procedure to well understand the procedure and the instructions, and the psychological self-report measures of mental fatigue were conducted. Subjects then performed the simulated driving without any break either until 150 min elapsed or until volitional exhaustion occurred. During the driving, subjects were asked to restrict all unnecessary movements as much as possible and to try their best to maintain constant speed and avoid car accidents. There were not any questionnaires and any additional measurements during driving, so as to maintain a monotonous condition. At the end of all experiment sessions, the same psychological self-report measure of fatigue was also carried out.

2.4. Data acquisition

The physiological signals were recorded by a Neruoscan system with international 10–20 lead systems. EEGs were recorded using a 32 channel electrode cap with sintered Ag/AgCl electrodes from scalp positions FP1, FP2, F7, F3, Fz, F4, F8, FT7, FC3, FCz, FC4, FT8, T7, C3, Cz, C4, T8, TP7, CP3, CPz, CP4, TP8, P7, P3, Pz, P4, P8, O1, Oz, O2 (Fig. 1). Vertical electrooculogram (EOG) was recorded using bipolar electrodes placed above and below the left eye. All sites were referenced to linked mastoids. The connecting impedance was kept below 5 kΩ. All physiological signals were sampled at 500 Hz with 0.05–70 Hz band-pass filter and 50 Hz notched. The EEG larger than +100 uV was rejected as artifact. Eye movement contamination of EEG was firstly removed by adaptive filtering methods.

Meijman (1994) reported that the length of preceding work hours had negative effects on mental fatigue by impairment of the mental performance capacity itself or by negative changes of the willingness to spend mental capacity in order to sustain an adequate performance. The conclusion was consistent with empirical evidence. In this study, the driving mental fatigue is classified into three levels: the alert, the medium fatigue and the extreme fatigue according to time-on-task. Thus epochs of the experimental beginning (0–15 min), the middle (75–90 min) and the end (135–150 min) are selected to investigate different mental fatigue states. After artifact detection and ocular correction, 30-s continuous EEG data of each epoch for each subject are selected to be analyzed.

During the whole simulative driving, the mental fatigue signs such as rubbing, yawning and nodding, the driving performances such as car accidents, flameout, and other operating errors are recorded manually by an observer to validate mental fatigue states.

2.5. EEG features extracted based on MVAR

MVAR model is the extension form of the univariate AR model and can capture data flowing from a number of channels simulta-

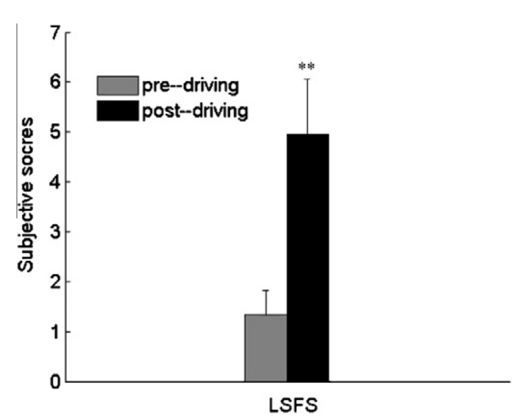

Fig. 1. The scores of self-report ($^{**}p < 0.005$).

neously. Analysis of the multichannel EEG with this method can be used in researching the synchronization of brain structures, the degree of coupling between channels, the estimation of phase delays, and eventually the direction of spreading of brain activity (Anderson et al., 1998; Franaszczuk et al., 1985; Neumaier & Schneider, 2001)

MVAR model with pth order can be expressed as:

$$\boldsymbol{v}_n = \sum_{i=1}^{p} \boldsymbol{A}_i \boldsymbol{v}_{n-i} + \boldsymbol{\varepsilon}_n, \boldsymbol{\varepsilon}_n = noise(\boldsymbol{C}) \tag{1}$$

where m-dimensional vector $\boldsymbol{\varepsilon}_n$ is the vector of multivariate zero mean uncorrelated white noise process and covariance matrix $\boldsymbol{C} \in \boldsymbol{R}^{m\times m}$, $\boldsymbol{A}_1, \boldsymbol{A}_2, \ldots, \boldsymbol{A}_p \in \boldsymbol{R}^{m\times m}$ are the coefficient matrices of the MVAR model. The vector $\boldsymbol{v} \in \boldsymbol{R}^m$ is a vector, which consists of sampling signal by m channels at n time. Eq. (1) shows that the multivariable signals at n time can be estimated by their values at past time and the white noise.

An AR model of a sequence of observations may be found by estimating the parameter matrices by way of a least squares procedure that minimizes the sum of squared errors. This is the Yule–Walker equations:

$$-[\boldsymbol{R}(1)\boldsymbol{R}(2)\cdots\boldsymbol{R}(p)] = [\boldsymbol{A}(1)\boldsymbol{A}(2)\cdots\boldsymbol{A}(p)]\widetilde{\boldsymbol{R}} \tag{2}$$

where

$$\widetilde{\boldsymbol{R}} = \begin{bmatrix} \boldsymbol{R}(0) & \boldsymbol{R}(1) & \cdots & \boldsymbol{R}(p-1) \\ \boldsymbol{R}^T(1) & \boldsymbol{R}(0) & \cdots & \boldsymbol{R}(p-2) \\ \vdots & \vdots & & \vdots \\ \boldsymbol{R}^T(p-1) & \boldsymbol{R}^T(p-2) & \cdots & \boldsymbol{R}(0) \end{bmatrix}$$

The solution of these equations is the coefficient matrices of the MVAR model.

Before coefficients calculating, the model order should be determined. The model order can be found by means of criteria derived from information theory. Previous research tested the sensitivity of MVAR performance depending on the model order and demonstrated that small changes of model order do not influence results. The Akaike's Information Criterion (AIC) was found as the most satisfactory for model order determination (Franaszczuk et al., 1985). It is used in this work for MVAR model fitting

$$\mathrm{AIC}(k) = N\log[\det(\widehat{\boldsymbol{V}}_e)] + 2m^2k \tag{3}$$

where N is the number of experimental data points of the sampled signal, m is the number of inputs (or channels in this case), $\widehat{\boldsymbol{V}}_e$ is the estimated covariance matrix of the noise processes. $\widehat{\boldsymbol{V}}_e$ can be determined from the formula:

$$\widehat{\boldsymbol{V}}_e = \boldsymbol{R}(0) + \sum_{i=1}^{k} \boldsymbol{A}_i \boldsymbol{R}(i) \tag{4}$$

where $\boldsymbol{A}_i$, $\boldsymbol{R}(i)$ are the estimated: matrix of coefficients and matrix of covariance.

After the optimal model order p is determined. Let $\widehat{\boldsymbol{D}}_k$ be the combined model coefficient matrix of the kth data segment

$$\widehat{\boldsymbol{D}}_k = (\widehat{\boldsymbol{A}}_{k,1}\widehat{\boldsymbol{A}}_{k,2}\cdots\widehat{\boldsymbol{A}}_{k,p}) \tag{5}$$

Then, feature vector can be constructed as follows:

$$\tilde{x}_k = (\widehat{\boldsymbol{D}}_{k,1:}\widehat{\boldsymbol{D}}_{k,2:}\widehat{\boldsymbol{D}}_{k,3:}\widehat{\boldsymbol{D}}_{k,4:}\widehat{\boldsymbol{D}}_{k,5:}\widehat{\boldsymbol{D}}_{k,6:})^T \tag{6}$$

where the coefficient vector $\widehat{\boldsymbol{D}}_{k,1:}$ represents the ith row of the matrix $\widehat{\boldsymbol{D}}_k$. The feature vectors obtained from all data segments will be saved for later analysis. In this study, EEG data of six electrodes (Fp1, Fp2, C3, C4, O1, O2) are selected for analyzing. According to AIC, the order of the MVAR is selected as 3. For a three-order model and six channels, the size of the feature vector is 108.

2.6. Kernel based dimensionality of feature space reduction

Before executing a learning algorithm, additional vector space transformations need to be applied on the initial features for improving classification performance and reducing the dimensionality of the data. Kernel principal component analysis (KPCA), proposed by Scholkopf, Smola, and Muller (1998), is one approach of generalizing linear PCA into nonlinear case using the kernel method. The basic idea is to map the original input vectors into a high-dimensional feature space and then to calculate the linear PCA in this feature space. KPCA as a nonlinear feature extractor leads to better classification than the linear ones. KPCA algorithm is used to reduce the dimensionality of EEG features and the Gaussian function is selected as the kernel function.

2.7. Multiclass support vector machine

Support vector machine (SVM), a novel machine learning algorithm, has been recently proven to be a promising tool for both data classification and pattern recognition (Vapnik, 1998). SVM is also a kernel-based classification technique that is based on the margin-maximization principle, which makes SVM have better generalization ability than the other traditional learning machines that are based on the learning principle of empirical risk minimization. SVM uses the kernel-mapping to map the data in input space to a high-dimensional feature space in which the problem becomes linearly separable. There are many kinds of kernels that can be used, such as the linear, polynomial and radial basis function (RBF) kernels (Zhang, Zhou, & Jiao, 2004). To reduce the search-space of parameter sets, in this study we train all datasets only with the RBF kernel.

The earliest used implementation for SVM multiclass classification is probably the one-against-all (OA) method (Simard & Vapnik, 1994). It constructs k SVM models where k is the number of classes. The ith SVM is trained with all of the examples in the ith class with positive labels, and all other examples with negative labels. Another major method is called the one-against-one (OO) method (Knerr, Personnaz, & Dreyfus, 1990). Assume training data from the ith and the jth classes. This method constructs $k(k-1)/2$ classifiers where each one is trained on data from two classes. If decision function says x is in the ith class, then the vote for the ith class is added by one. Otherwise, the jth is increased by one. Then we predict x is in the class with the largest vote. The decision strategy is called "Max Wins".

In this study, two multiclass SVM methods also are adopted to identify the three driving mental fatigue states.

3. Results

3.1. Self-report about driving mental fatigue

The subjective component of fatigue is very important, questionnaire investigations may be important in the study of driver mental fatigue. Questionnaires can provide information about fatigue such as the feelings when fatigue appeared and factors contributing to fatigue. According to the self-report questionnaires, all the subjects felt tired, bored and drowsy when the driving task was over. They also reported that these feelings became stronger and there were difficulties to concentrate and focus their attention on the driving task as the driving time increased. To keep the monotonous driving environment, the questionnaires just only were carried out at two epochs: pre-driving: before driving task; post-driving: after that task. Fig. 1 shows the psychological self-report measures of mental fatigue according to Li's subjective fatigue scale (LSFS) (Li, Jiao, Chen, & Wang, 2003).

The self-report questionnaires revealed subjects as almost not fatigued before the driving task and moderately to extremely fatigued after driving. Compared with the pre-driving, the subjective scores increased significantly ($t = -9$; df = 9; $p < 0.001$) after the end of the driving.

3.2. Some objective indicators of driving mental fatigue

To maintain scientific validity, questionnaires should not be the sole identifier of fatigue symptoms. More objective measures need to accompany them for verification of fatigue. The subject's mannerisms such as rubbing, yawning and nodding, the driving performance details such as car accidents, flameout, and other operating errors and the vertical EOG were combined to validate the different driving mental fatigue status. The EOG was used to identify blink artifact in the EEG data as well as changes in blink types such as the small and slow blinks that characterize fatigues.

Table 1 shows the proportion of subjects categorized according to the mannerisms identified from the manually recorded data as well as the driving performance in each state. There almost are not fatigue physical mannerisms during alert states. Over 60% subjects showed fatigue physical mannerisms during medium state. In extreme state, these mannerisms are observed in all subjects. The lapse of driving proportion also increases linearly from alert to extreme fatigue state.

In Table 1, each validated mannerisms for subjects should satisfy these criterions respectively: 1 Rubbing/5 min; 1 Yawn/5 min; 1 Noddings/30s; 1 Flameout/7.5 min; 1 Car accidents/7.5 min; 1 Other driving errors/15 min.

The blink frequency can be estimated by EOG. The data of blinks were obtained from EOG by identifying the peak of blink based on wavelet detection method. Fig. 2 shows the blink frequency at the three mental fatigue states.

The blink frequency is increasing from alert to extreme state. The ANOVA results show a highly significant difference in the three mental fatigue states. ($F(2, 18) = 8.876$, $p = 0.002$;). The least difference (LSD) post hoc analysis shows that the alert state is significant different from medium and extreme fatigue states, but there is no statistical difference between medium and extreme fatigue states.

Table 1
The mannerisms of fatigue and lapses in driving performance.

Mannerisms	Alert (%)	Medium fatigue (%)	Extreme fatigue (%)
Rubbing	10	60	100
Yawns	0	70	100
Noddings	0	70	100
Flameout	0	30	80
Car accidents (collisions)	0	60	90
Other driving errors	0	40	70

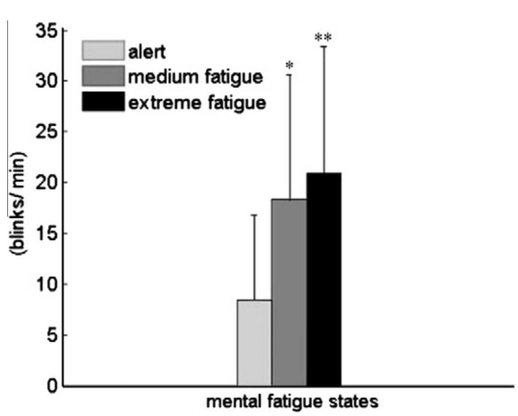

Fig. 2. The blink frequency of three fatigue states ($^{*}p < 0.05$; $^{**}p < 0.005$).

3.3. The classification results

The subjective and objective measures indicate that driving mental fatigue is induced after a long time simulative driving task. In order to distinguish different mental fatigue states, 30 s EEG data of each subject in three epochs are selected to be analyzed. The EEG data is divided into 2 s segment with 0.2 s overlapping. The sample set includes 420 data segments for each subject. As the number of EEG data segment available is limited in this experiment, a 27-fold cross-validation test is applied. For each subject, the 20% of this sample set is selected as testing set and the 80% is selected as training set randomly, the classification accuracy is calculated over 27 trials with different random selection of training and testing set.

For a three-order MVAR model and six channels, the size of the EEG feature vector is 108. KPCA is applied to reduce the size of feature vectors and then the lower-dimensional vectors are considered as input of SVM. The test performance of the classifiers can be determined by the computation classification accuracy which is defined as the proportion of the correct decisions number and total cases number.

When KPCA is applied to reduce the dimension of features, Gaussian function is selected as the kernel function. Fig. 3 shows the average accuracy with different kernel parameter σ.

From Fig. 3, we also find that the kernel parameter σ is a factor which can influence classification accuracy. The max-accuracy reaches 80.8% when σ equals to 1.

The average classification accuracies of all subjects under different numbers of the feature dimensions are illustrated in Fig. 4.

Fig. 4 shows that classification accuracy fluctuates with the number of feature dimension. The max-accuracy achieves 81.64% when the number of features equals 25. The classification results do not improve with the features dimension increasing.

In this study, the classification accuracy is obtained by averaging the classifying result of the three-classes. Fig. 5 represents the classifying result about different mental fatigue states over all subjects.

Fig. 5 shows that the max-accuracy about three mental fatigue states has some difference. The alert and extreme fatigues obtain a slightly higher accuracy than medium fatigue state. The max-accuracy is alert 81.6%, medium 80%, extreme 83.8% respectively.

As a basis for comparison, we observe the accuracy of classification under the condition of the various extraction features using

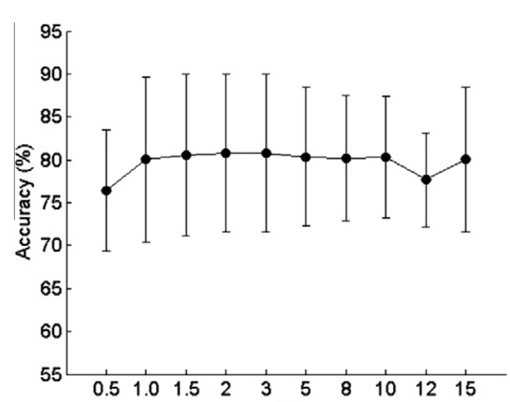

Fig. 3. The classification accuracy under different σ.

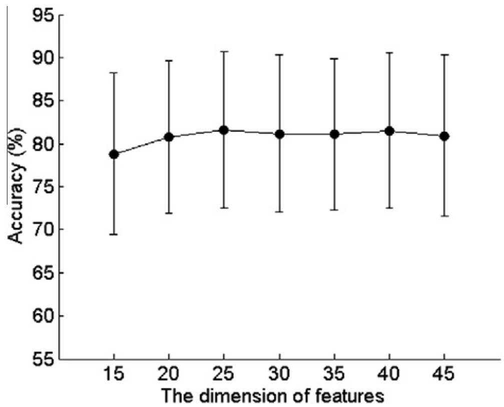

Fig. 4. The classification accuracy under different feature dimensions.

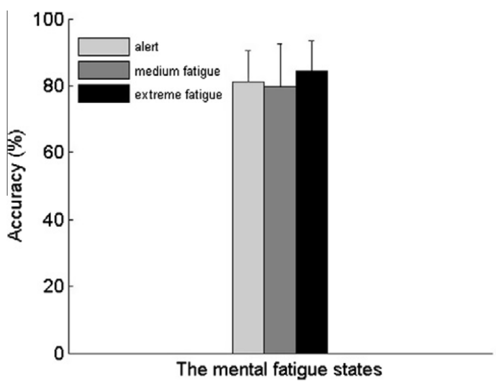

Fig. 5. The classification accuracy of three fatigue states.

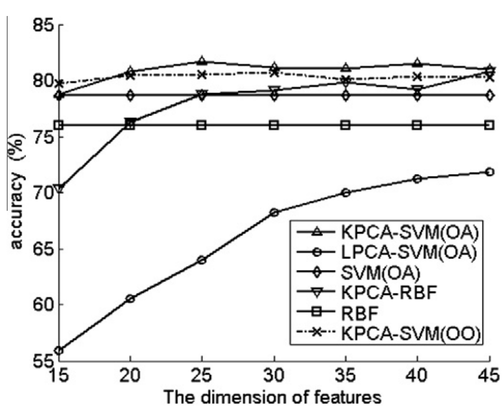

Fig. 6. The comparison of different classification algorithms.

KPCA and linear PCA (LPCA) respectively. And we also compare the results to the original SVM without using KPCA or LPCA, the original RBF network and KPCA–RBF network classification. In addition, the accuracy of two kinds of multiclass SVM (OA and OO) is contrasted when applying KPCA. Fig. 6 shows the classification result of various algorithms under different numbers of the feature dimensions.

From Fig. 6, it can be found that KPCA–SVM shows the best performance with the highest accuracy. The maximal classification accuracy achieves 81.64% while the number of feature dimensions equals 25. Although the feature-vector dimensions are reduced by KPCA, the accuracy is better than SVM with high-dimension original feature data. However, the result of LPCA–SVM is not desired and the classification accuracy is below 72%. Compared with LPCA–SVM, the accurate rate of KPCA–SVM is improved significantly. For multiclass SVM, the result based on OA method is better than that of OO method on the whole. For the original non-reducing feature dimensions data, the SVM takes the better performance than that of RBF network. Furthermore, KPCA–RBF shows better performance than that of RBF with high-dimension original feature data while feature dimensions is more than 20. Table 2 compares the performance of KPCA–SVM with the other types of classification algorithm under different number of feature dimensions.

In Table 2, it can be seen that the max-accuracies do not belong to one fixed dimension for different classification algorithms. When the number of features dimension is reduced by KPCA, the fewer dimension combines with the faster speed of classifying, we should balance the best performance and the classification speed.

Compared with the original SVM, the KPCA–SVM can accelerate the classification speed and accuracy of driving mental fatigue effectively, which greatly reduces the dimensionality of input features. Moreover, the performance of KPCA–SVM is greater or more than that of LPCA–SVM and RBF network. KPCA–SVM is a promising classifier for driving mental fatigue.

4. Discussion

It is well known that there is a strong link between time-on-task and mental fatigue progression. Many studies have demonstrated this validity (Otmani, Pebayle, Roge, & Muzet, 2005; Ting, Hwang, Doong, & Jeng, 2008). The self-report results in our study revealed that subjects were slightly fatigued before and moderately or extremely fatigued after the driving test. Lal and Craig (2002) used subject's mannerisms and EOG signs as independent variables to identify different mental fatigue phases with excellent reliability and satisfying result. In this present experiment, the mannerisms of fatigue and lapses in driving performance are absent at the start of task and increase with time-on-task till almost all subjects showed these signs at the end of the task. According to the statistical results, mental fatigue mannerisms and collisions accidents have occurred across over 60% subjects under medium fatigue status. This should be the notable symbol of increased mental fatigue. The time-on-task actually has a negative effect on driver's performances and behaviors. The result of blink frequency also indicates that they are significantly different among three epochs. The conventional blinks during the alert phase are replaced

Table 2
The comparison of the accuracy (%) of different number of feature dimensions.

Algorithm	The number of features dimension							The max-accuracy
	15	20	25	30	35	40	45	
KPCA–SVM(OA)	78.80	80.83	81.64	81.18	81.10	81.52	80.96	81.64
PCA–SVM	55.96	60.54	64.01	68.19	70.04	71.21	71.82	71.82
SVM	78.71	78.71	78.71	78.71	78.71	78.71	78.71	78.71
KPCA–RBF	70.37	76.26	78.77	79.15	79.80	79.24	80.23	80.23
RBF	76.06	76.06	76.06	76.06	76.06	76.06	76.06	76.06
KPCA–SVM(OO)	79.72	80.44	80.51	80.70	80.10	80.32	80.24	80.70

by fast rhythmic blinks during mental fatigue. The blink frequency increases positively with the extent of mental fatigue. This result is consistent with that Lal and Craig (2002) reported.

In this experiment, the classification accuracy of medium fatigue is slightly lower than those of alert and extreme fatigue states. To three-class problem, the lower classification accuracy in one class means this class sample is similar to one of the rest samples. This result suggests that medium state might lie between alert and extreme state.

It has been known for many years that the change in brain arousal involves specific changes in oscillatory brain activity and the EEG can reflect the fluctuation of alertness level. The EEG signal may be one of the most predictive and reliable index to assess mental fatigue. However, there are different EEG rhythm changes on different scalp regions during mental fatigue. Jap et al. (2008) also made the same conclusion. It is necessary to look at activity distributed over the entire scalp in order to detect brain state changes. Previous study also indicated that the application of multivariate approach for the determination of the information flow in brain structures brought very rich and important information about the interactions between brain structures (Franaszczuk et al., 1985; Kus, Blinowska, Kaminski, & Basinska-Strarzycka, 2005). In this study, EEG data of six electrodes (Fp1, Fp2, C3, C4, O1, O2) were selected for analyzing. MVAR model is employed to extract model coefficients as EEG features. The model can give us the information on the mutual relationships between relevant structures, particularly on the degree of their synchronization in the frequency domain. The features extracted by MVAR should be sensitive to the change of driving mental fatigue. One can see when looking at the averages across subjects that the MVAR gives the best three-states classification accuracy at 81.64%.

For the high-dimensions of extracted feature by MVAR, KPCA method is applied to reduce the dimensions of feature vectors. KPCA is a generalization of PCA in a feature space by a kernel function that could be nonlinear. Compared with LPCA, KPCA can extract more efficient features that are useful for the classification purpose. That is why the results become better when LPCA is replaced by KPCA.

The performance of SVM classifier is nonsensitive to the sample size and the dimensionality. In addition, its ability to produce stable and reproducible results makes it a good candidate for solving many classification problems (Burges, 1998). In this paper, the SVM shows more excellent results than RBF network under the same dimensions. The classification abilities of two kinds of SVMs, respectively trained by OA and OO method, are further compared. The experimental result proves that OA method is better in achieving the generalization ability of the SVM for three-class problem.

Combined KPCA with SVM, obtains the best performance with the highest average accuracy over all subjects. The classification results indicate that KPCA–SVM show better performance than that of original SVM with high-dimension original feature data even the dimensions of feature vector are few. KPCA method could significantly reduce the dimensions of the feature vectors in a high-dimensional feature space by a nonlinear mapping. The low-dimensional feature representation preprocessed by KPCA would accelerate the speed and improve the accuracy of the classifier. The KPCA–SVM can obtain the satisfying accuracy in classifying three-level driving mental fatigue with the lower dimensions of feature space.

5. Conclusion

Driving mental fatigue is a complicated physiological and psychological process. This paper presents a framework based on EEG for classifying driving mental fatigue. The MVAR extract EEG features effectively which are sensitive to the change of driving mental fatigue. Then the kernel-based algorithm KPCA leads to better classification and faster calculation speed for its nonlinear transformations and feature vector dimensions reduction capacity. The experimental results show that KPCA–SVM algorithm enhances the generalization ability of the classifier and improve the accuracy of driving mental fatigue states recognition. The classifying model could be potential for evaluating driving mental fatigue.

However there are two factors that play important roles in classification, the kernel parameter σ and the number of feature vector dimensions. The two factors corresponding to the best accuracy of each subject are different. It is still a further ongoing research issue that is how to choose the optimal kernel parameter σ and the number of feature vector dimensions in order to take the higher classification accuracy.

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