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Can SVM be used for automatic EEG detection of drowsiness during car driving?

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Mervyn V.M. Yeo [a], Xiaoping Li [a,b,*], Kaiquan Shen [b], Einar P.V. Wilder-Smith [c]

[a] Division of Bioengineering, National University of Singapore, 9 Engineering Drive 1, Singapore 117576, Singapore
[b] Department of Mechanical Engineering, National University of Singapore, 9 Engineering Drive 1, Singapore 117576, Singapore
[c] Division of Neurology, National University of Singapore, 9 Engineering Drive 1, Singapore 117576, Singapore

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Abstract

困倦的开始

This study aims to develop an automatic method to detect drowsiness onset while driving. Support vector machines (SVM) represents a superior signal classification tool based on pattern recognition. The usefulness of SVM in identifying and differentiating electroencephalographic (EEG) changes that occur between alert and drowsy states was tested. Twenty human subjects underwent driving simulations with EEG monitoring. Alert EEG was marked by dominant beta activity, while drowsy EEG was marked by alpha dropouts. The duration of eye blinks corresponded well with alertness levels associated with fast and slow eye blinks. Samples of EEG data from both states were used to train the SVM program by using a distinguishing criterion of 4 frequency features across 4 principal frequency bands. The trained SVM program was tested on unclassified EEG data and subsequently checked for concordance with manual classification. The classification accuracy reached 99.3%. The SVM program was also able to predict the transition from alertness to drowsiness reliably in over 90% of data samples. This study shows that automatic analysis and detection of EEG changes is possible by SVM and SVM is a good candidate for developing pre-emptive automatic drowsiness detection systems for driving safety.

Keywords: Alert; Drowsy; Driving; EEG; SVM; Pattern recognition

1. Introduction

Drowsiness while driving is a serious problem and is believed to be a direct and contributing cause of road related accidents. This would endanger the lives of the driver and passengers, and could cause serious accidents along major roads (Lal and Craig, 2001). If symptoms of drowsiness could effectively warn drivers, corrective measures could be taken and disastrous outcomes prevented.

The objective of this study is to establish an automatic method of distinguishing between alert and drowsy states by using a recently established signal pattern recognition technology to develop a reliable detection system of drowsiness for driving safety.

There is a general agreement that visual inspection of EEG waveforms and eye blink patterns can reliably identify driver fatigue or drowsiness (Brown, 1967; Chase, 2000; Dureman and Boden, 1972; Hulbert, 1972; Mast et al., 1966; Naatanen and Summala, 1978; Skipper and Wierwille, 1986; Stern et al., 1984; Summala et al., 1999). Computer-based EEG classification of drowsiness has been analyzed in several studies, either by EEG signal pattern recognition (Makeig and Jung, 1996; Gevins and Smith, 1999), or by spectral analysis of EEG recordings (Jung and Makeig, 1994; Makeig et al., 1996; Jung et al., 1997; Doghramji et al., 1997). Principe et al. (1989) were one of

* Corresponding author. Address: Division of Bioengineering, National University of Singapore, 9 Engineering Drive 1, Singapore 117576, Singapore. Tel.: +65 6516 3429; fax: +65 6779 1459.

E-mail addresses: engp1901@nus.edu.sg (M.V.M. Yeo), mpelixp@nus.edu.sg (X. Li), mpeskq@nus.edu.sg (K. Shen), mdcwse@nus.edu.sg (E.P.V. Wilder-Smith).

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the earlier investigators to design a finite automation to categorize sleep into seven different stages. McKeown et al. (1997) used statistical methods of analyzing EEG signals to detect vigilance changes.

Previous studies have tracked driver sleepiness in a driving simulator by analyzing EEG and driving performance. Drivers cannot maintain a high level of alertness when they are mentally fatigued and this has been shown to be associated with consistent and reliable changes in delta, theta, and alpha activity (Lal and Craig, 2000a, 2000b). Ambulatory studies with nonprofessional drivers have further demonstrated cortical deactivation in response to continuous and monotonous driving (Brookhuis and De Waard, 1993; De Waard and Brookhuis, 1991). Furthermore, researchers have also found associations between EEG delta, theta, alpha, beta, sigma waves and drowsiness during driving (Caille and Bassano, 1977; Lal and Craig, 2000a, 2000b; Torsvall and Akerstedt, 1983, 1987). Most previously published studies on EEG changes during drowsiness provide varying results due to significantly different methodology and purpose of study. Hence, a robust experimentally controlled study is required to identify and clarify the EEG changes that occur during periods of alertness and drowsiness whilst driving.

Studies by Yeo et al. (2007), Eoh et al. (2005), Thiffault and Bergeron (2001), Liang et al. (2005) and Moller et al. (2006) have agreed that the study of sleep onset while driving differs from normal sleep studies as the passage from wakefulness to sleep is resisted and the subject struggles to maintain vigilance. Lin et al. (2005) demonstrated that an EEG-based drowsiness estimation system that combines EEG log sub-band power spectrum, correlation analysis, principal component analysis, and linear regression models is feasible to accurately estimate driving performance quantitatively (expressed as deviation between the center of the vehicle and the center of the cruising lane) in a realistic driving simulator.

In the study of drowsiness, the transition period between relaxed wakefulness and the onset of drowsiness is associated with Hori's sleep stage 1 (Hori et al., 1994), i.e. the first appearances of EEG alpha dropouts from predominant beta activity. Automatic drowsiness detection systems have previously been developed by tracking driving and eye blink duration (Verwey and Zaidel, 2000; Virkkala et al., 2007). The computerized and automatic analysis of EEG recordings has been well established with the use of modern technologies such as the artificial neural network (ANN). Wilson and Bracewell (2000) developed a method of detecting the alert state by applying a wavelet preprocessing and an ANN, and used a binary output (alert and drowsy states). Vuckovic et al. (2002) were one of the first groups to use ANN as an automatic classifier of alertness and drowsiness from EEG recordings on arbitrary normal subjects. In this study, we propose a recently established technology similar to ANN to classify and predict EEG drowsiness.

The support vector machines (SVM) has been a well known learning method (Boser et al., 1992; Cortes and Vapnik, 1995; Vapnik, 1995; Cristianini and Shawe-Taylor, 2000). A remarkable property of SVM is its good generalization capacity independent of the input space dimension (Cristianini and Shawe-Taylor, 2000). This makes SVM well suited for the analysis of biomedical data, such as multi-channel EEG recording, where many features can be redundant due to inherent redundancy of the data. Hence, SVM has recently been applied to many biomedical problems, like gene identification of various cancerous tumors using gene expressing data (Guyon et al., 2002; Weston et al., 2001) and automated diagnosis system using EEG (Acir et al., 2005).

There has been recent work on developing countermeasure mechanisms on driver-related fatigue. Lal et al. (2003) were the first to develop software to detect fatigue based on EEG changes in all frequency bands. They classified fatigue into 4 phases: early, medium, extreme fatigue phases, and an arousal phase, according to video analysis of facial features and the electro-oculogram (EOG) outcomes. The algorithm was developed using LabView which is capable of analyzing EEG data in real time and off-line analysis of previously acquired data.

In this study, SVM is used as a classification tool to process and interpret EEG data for the detection of driving drowsiness. A classification task usually involves training and testing data which consist of some data instances. Each instance in the training set contains one 'target value' (class labels) and several 'attributes' (features). The goal of SVM is to produce a model which predicts the target value of data instances in the testing set with only the attributes provided.

This study aims to enable SVM to establish an automatic method of distinguishing between alert and drowsy states, hence developing a reliable detection system of drowsiness for driving safety. To achieve this, measurable characteristics in the EEG signal, particularly signal frequency parameters that correlate with alertness and drowsiness states, will be identified and used as the chief sources for pattern recognition.

2. Methods

2.1. Support vector machines (SVM)

SVM is a supervised learning method used for classification and regression. Unlike other statistical learning methods (such as neural networks and decision trees) which usually aim only to minimize the empirical classification error, SVM simultaneously minimizes the empirical classification error and maximizes the geometric margin in classification. This is done by constructing a hyperplane which optimally separates samples from two classes (for minimum empirical classification error) with maximum margin (for maximum classification margin); hence it is also known as maximum margin classifier (Boser et al., 1992;

Cortes and Vapnik, 1995; Vapnik, 1995; Cristianini and Shawe-Taylor, 2000). The basic principles of SVM for classification are briefly discussed in this subsection, whereas its detailed mathematical description is given in the Appendix.

The training of SVM is essentially finding the aforementioned separating hyperplane using the training data set, but the trick is to find the hyperplane in a high (possibly infinite) dimensional space obtained by transforming the original feature space using an appropriate nonlinear mapping function, rather than in the original feature space. This is motivated by the fact that the samples from two classes can always be separated by a hyperplane with an appropriate nonlinear mapping function to a sufficiently high dimension (Duda et al., 2001). Fig. 1 shows an illustrative example of a hyperplane that SVM constructs. The support vectors of SVM are the training samples that define the optimal separating hyperplane and are the most difficult patterns to classify (see Fig. 1). These support vectors are the most informative for the classification task. The SVM firstly identifies these support vectors and then constructs the optimal separating hyperplane which optimally separates two classes with maximum margin. That is the machine training for SVM.

As a classifier, for a given unseen feature vector (corresponding to a point in the transformed space), the trained SVM outputs its predicted class label based on the half space (defined by the hyperplane) to which that feature vector belongs.

2.2. Participants

The recruitment of human subjects for this study was approved by the National University of Singapore (NUS) ethical committee. Human subjects were recruited from the students of NUS. The subjects were screened by completing a sleep questionnaire to assess their natural sleep conditions and periods. The Epworth Sleepiness Scale (ESS) (Johns, 1991) was used to pre-screen and determine the level of daytime sleepiness. It was administered between 1 and 7 days prior to testing. The ESS scale ranges from 0 to 24 and scores below 10 are classified as having no daytime sleepiness. As this study preferred subjects without overtly increased sleep pressure in the day whilst not being too resistant to sleep at the same time, subjects with Epworth scores between 8 and 9 were hence selected for this study. Subjects were required to keep a sleep diary one week prior to the experiment to ensure that they had at least 7 h of continuous sleeping time and regular sleeping hours (going to bed no later than 1 am and waking up by 9 am). Subjects were required to adhere to these strict instructions to be included into the study. Those selected were compensated a token sum of S$80 to cover the miscellaneous costs associated with this study.

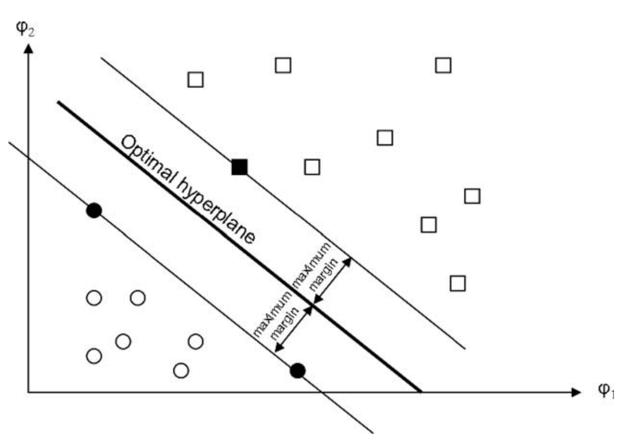

Fig. 1. Training of SVM is to find the optimal hyperplane (thick solid line) which separates the samples from two classes (circles vs. squares) with maximum margin. The support vectors are shown as solid circles or squares. The figure shows the projection view of the hyperplane in two dimensions (φ_1 and φ_2) in the transformed space.

Twenty healthy tertiary students at local universities (10 males, 10 females) with car driving licenses were selected to take part in this study, ages ranging from 20 to 25 years. No alcohol, caffeinated drinks and drowsiness-causing medications were to be consumed the day before each test.

2.3. EEG equipment and data collection

The EEG equipment used was a 32-channel Medtronic PL-Winsor 2.35 system, with a sampling frequency of 256 Hz, an integrated low pass (cut-off frequency of 35 Hz) and a time constant of 0.30 s. Full head mapping was done using the standard 10/20 system of electrode placement (Jasper, 1958). EEG Bipolar recordings using the ‘double banana’ bipolar referencing montage with 19 channels were carried out in all the tests to reduce pulse artifacts caused by heartbeat pulses. EOG recordings were performed by attaching an electrode above each eye. EOG data was used to analyze eye blink patterns as part of the manual classification criteria for classifying EEG alertness and drowsiness.

2.4. Driving simulation tasks

Each subject underwent simulated driving tests at 3 pm, which corresponded to the afternoon sleepiness peak in the human circadian rhythm (De Gennaro et al., 2001). Simulated driving tests (George, 2003) consisted of a video clip showing moving road images of straight, monotonous highways mostly free of vehicles shown from the perspective of a driver while operating a car. Monotonous car engine sounds were continuously playing in the background. Subjects were acting as drivers on a simulated driving platform and were instructed to behave as though driving along a highway and to watch the road at all times. Simulated driving lasted 1 h in which the driver’s attempts at maintaining vigilance were dependent on their own determination to stay awake. EEG was continuously recorded, there was no feedback on driving errors, thereby reducing external disturbances and providing an environment conducive to sleep.

2.5. Data preparation

EEG pulse artifacts and epochs containing movement artifacts from the raw EEG data were removed by visual inspection. In addition, a customized bandpass filter with a pass band of 0.1–25 Hz implemented in Matlab (version 6.5, MathWorks, USA) was used in preprocessing the collected raw EEG data. They were then manually classified into 'alert' and 'drowsy' classes by two of the authors as raters who are trained in interpreting the EEG. Agreement was based on a detailed visual inspection approach adopted by Kellaway (1990) using two key identifiers (Yamada, 1998): (1) eye blink patterns and (2) dominant EEG activity. The EEG data were scored in 10-s epochs based on the following criteria.

In this study, the definitions of alertness and drowsiness states follow closely with Hori's criterion at a more specific level. The 'alert' state refers to relaxed wakefulness operationalized in EEG as the alert wakefulness with dominant beta activity (13–25 Hz) present, eye blinks of 0.3–0.4 s durations (Hart, 1992) and inter-eye blink intervals of 6–8 s (Doughty, 2002). The 'drowsy' state is operationalized as EEG showing the presence of slow eye movement with occipital alpha rhythm (9–13 Hz), a decrease in the amplitude and/or frequency of the alpha rhythm (alpha dropout), and eye closures greater than 0.5 s (Dinges et al., 1998; Santamaria and Chiappa, 1987).

To classify an epoch as 'alert', EEG signals would need to display all of the following characteristics:

1. Eye blink artifacts of 0.3–0.4 s durations and inter-eye blink intervals of 6–8 s.
2. EEG activity in the beta frequency.

To classify an epoch as 'drowsy', EEG signals would need to display at least one of the following characteristics:

1. Eye closures greater than 0.5 s.
2. More than 50% of EEG data showing occipital EEG alpha activity.
3. Appearance of alpha dropout events.

Each of the raters inspected the EEG recordings using the above criteria, and then agreed which epochs clearly indicate a drowsy or alert state of a subject. There were epochs where there were disagreements, especially in the identification of alpha dropout events: diffuse slowing of alpha activity without amplitude decrease, and appearing in very short intervals (<1 s), which would arouse ambiguity. The epochs with ambiguities were excluded from the analysis.

The manually classified experimental EEG data segments of 10-s epochs agreed by both raters were evenly split into two sets (training and testing), each containing a mixture of 'alert' and 'drowsy' EEG epochs. The SVM performance was assessed on both the training and the testing sets.

2.6. Feature extraction

As in most machine learning systems, feature extraction is needed. In this study, feature extraction was done by transforming each afore-mentioned 10-s EEG epoch into a feature vector (for data mining purposes). The purpose of feature extraction in the present study was to extract a set of features that optimally distinguish 'alert' EEG from 'drowsy' EEG. The proposed features were based on the power spectrum of each 10-s EEG epoch. Various features were extracted based on the power spectrum of EEG epochs, capturing both spatial and temporal information that were useful for distinguishing 'alert' and 'drowsy' EEG epochs.

Specifically, a fast Fourier transform (FFT) with a Hann window using 256 data points with 50% overlap was performed on each channel of a 10-s EEG data epoch. The resulting power spectrum density function $P(f)$ (normalized by its total power) was then divided into 4 segments according to the 4 standard EEG frequency bands: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–20 Hz). Then, the following four features were extracted for each frequency band:

2.6.1. Dominant frequency

For every peak in a considered frequency band, two frequencies in relation to the peak were defined – one was on the rising slope and the other was on the falling slope having the power equal to (or closest to) half the power of the peak. These two frequencies defined a frequency zone called full width half maximum band of the peak (Weisstein, 2006). It is worth noting that, if a peak is at the left (or right) edge of the considered frequency band, the rising (or falling) slope of the peak reduces to only one point, i.e. the peak itself. In such case, the corresponding frequency of the peak is used as the afore-mentioned frequency in the rising (or falling) slope in defining the full width half maximum band of that peak. Among all peaks in the considered frequency band, the peak with the largest average power in its full width half maximum band was called the dominant peak, while its corresponding frequency was called dominant frequency. In loose terms, this feature was to capture the dominant peak with the most significant bandwidth within a considered frequency band.

2.6.2. Average power of dominant peak

This was defined as the average power on the full width half maximum band of a dominant peak. It represented the significance/importance of that dominant peak.

2.6.3. Center of gravity frequency (CGF)

It was defined as

$$\mathrm{CGF} = \left[\sum_i P(f_i) \times f_i\right] \Bigg/ \left[\sum_i P(f_i)\right], \tag{1}$$

where f is frequency and $P(f_i)$ is the estimated power spectral density. This feature is significantly different from the first feature (dominant frequency), which can be illustrated by an example: if the spectrum for a considered frequency band is dominated by two narrow peaks (one larger than the other), it is not difficult to see from (1) that the center of gravity frequency will fall in between these two peaks, whereas the dominant frequency will be the frequency of the largest peak.

2.6.4. Frequency variability (FV)

It was defined as

$$\mathrm{FV} = \frac{\sum_i P(f_i) \times f_i^2 - \left[\sum_i P(f_i) \times f_i\right]^2 / \sum_i P(f_i)}{\sum_i P(f_i)}. \quad (2)$$

Considering $P(f_i)$ as the probability distribution of frequency, this feature is in fact the variance of the frequency in the defined frequency band.

As a result of the feature extraction, each 10-s EEG epoch in the afore-mentioned training and testing sets was converted into a 272×1 vector of quantitative EEG features (4 kinds of features $\times$ 17 channels $\times$ 4 frequency bands).

2.7. SVM for automatic EEG prediction of drowsiness

In this study, SVM was used for the purpose of automatic classification between 'alert' and 'drowsy' EEG epochs after initial feature extraction. The trained SVM was tested using the testing set of EEG data to evaluate its accuracy in distinguishing between 'alert' and 'drowsy' EEG. The trained SVM program was also tested for its accuracy and reliability in identifying the 'switching point' from alertness to drowsiness across individual experimental data. Data sequences which corresponded to transitions of alertness to drowsiness phenomena were extracted from the experimental dataset. Each sequence was broken down into 10-s epoch sub-segments. The SVM program was used to test each of these sub-segments, giving an output of either an 'alert' classification or a 'drowsy' classification. These sub-segments were re-combined to locate the 'switching point' at which the SVM program had identified along the data segment. Using this testing method, the 'switching point' would be measured in 10-s epoch divisions. This 'switching point' identified by the SVM program would be compared to manual classification, of which one of three outcomes could occur:

Relative to manual classification, the SVM program could identify the 'switching point' at:

1. the same epoch as manual scoring (this would be considered as a 'correct' predictor),
2. earlier epochs (this would be considered as an 'early' predictor), or
3. later epochs (this would be considered as a 'delayed' predictor).

3. Results

During the simulated driving tests all subjects at least fell into stage one sleep according to Rechtschaffen and Kales's criteria (Rechtschaffen and Kales, 1968). After manually scoring the EEG data from each test, it was observed that the EEG from all the tests consisted of alert and drowsy episodes, and sometimes including sleep episodes. Alert episodes comprised a mean percentage of 8% (SD: 2 min) of total experiment time, while drowsy episodes made up an average of 22% (SD: 6 min). For the rest of the experiment time, the subjects were either in a state of deeper drowsiness or had gone into light sleep. A manually scored EEG from a typical driving simulation session is illustrated in Fig. 2.

EEG data manually classified under the 'alert' state was predominantly in the beta frequency range, with eye blink durations falling between 0.2 and 0.35 s, and time between blinks averaged at 2–3 s. A sample of raw EEG data from the 'alert' state is shown in Fig. 3.

EEG data manually classified under the 'drowsy' state consist of eye blink durations between 0.5 and 1.5 s, with predominant alpha wave frequency activity and alpha dropout occurrences. A sample of raw EEG data from the 'drowsy' state is shown in Fig. 4.

After manual classification, the total number of 'alert' EEG segments of 10-s epochs classified by two raters was 483 and 494, respectively. Of these, 478 'alert' epochs were agreed by both raters and the remaining 21 'alert' epochs were discarded due to disagreements by the raters. Similarly, the total number of 'drowsy' EEG segments of 10-s epochs classified by two raters was 1424 and 1421, respectively. Of these, 1404 'drowsy' epochs were agreed by both raters and the remaining 37 'drowsy' epochs were discarded due to disagreements by the raters. The SVM training set consisted of 239 epochs of alertness and 702 epochs of drowsiness, and the testing set consisted of 239 epochs of alertness and 702 epochs of drowsiness.

To evaluate the performance of the trained SVM in distinguishing 'alert' and 'drowsy' EEG, the trained SVM

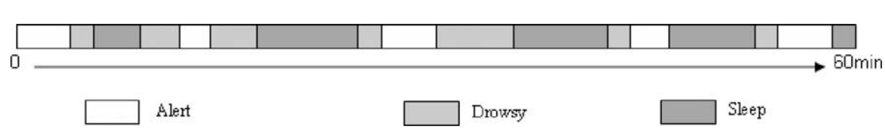

Fig. 2. Alert, drowsy and sleep episodes as scored by EEG manually from a typical 1-h driving simulation.

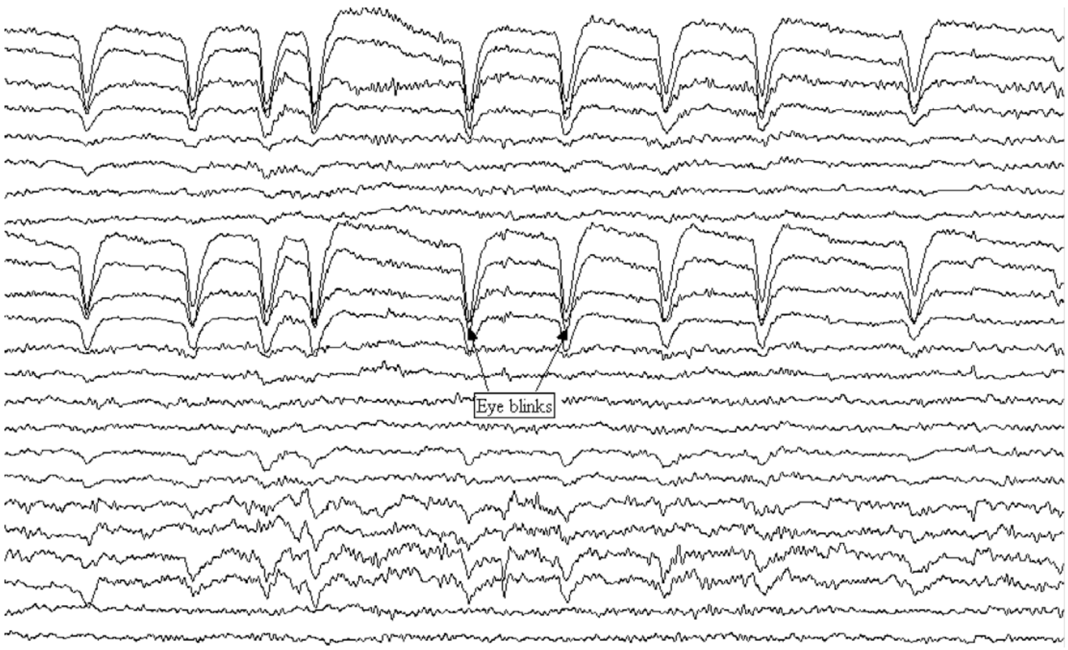

Fig. 3. Sample of raw EEG data manually classified as ‘alert’ (mean eye blink duration: 0.3 s, mean inter-blink period: 2 s, background beta EEG activity).

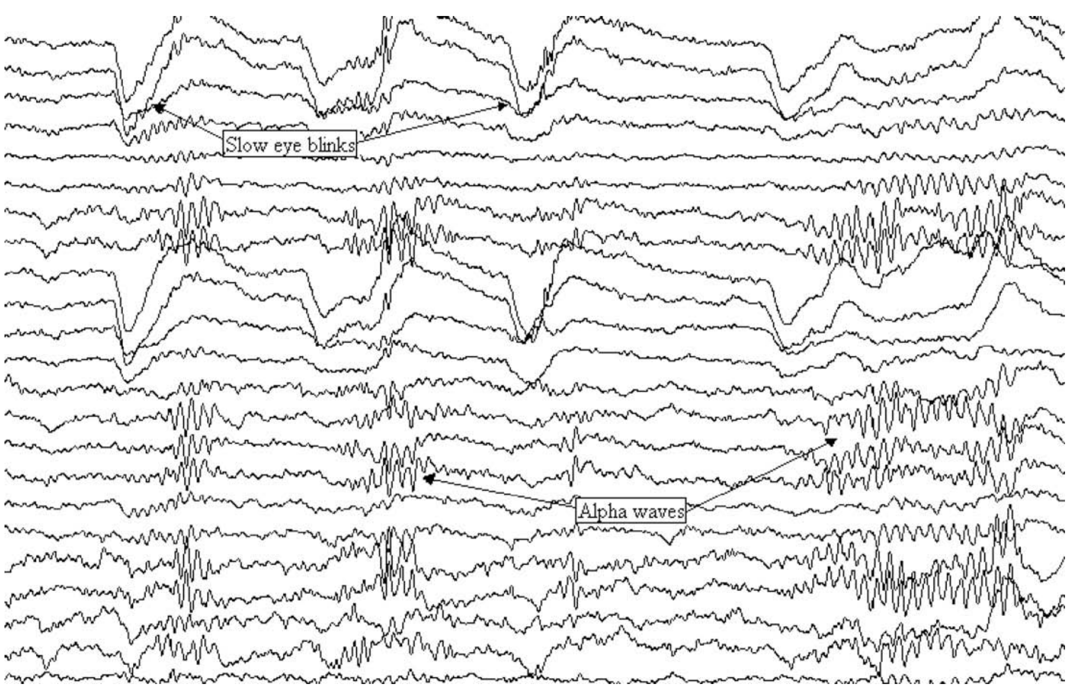

Fig. 4. Sample of raw EEG data manually classified as ‘drowsy’ (mean eye blink duration: 1 s, dominant alpha activity).

was tested using the testing set which has not been used in training. It achieved an accuracy of 99.30%. The accuracy was calculated in terms of percentage of correct classifications by SVM (compared to the manual classification). This indicates that a machine learning algorithm (SVM) is able to differentiate between EEG patterns associated with ‘alert’ vs. ‘drowsy’ states, and that the discriminative power of the computer software system is comparable to that of EEG experts using visual inspection.

In comparing the ‘switching point’ from alert to drowsy EEG between SVM and manual classification methods, the results from this test showed that, out of

49 EEG segments containing the transitions of alertness to drowsiness, the trained SVM gave 'correct' predictions in 37 of the segments (75%), 8 segments of 'early' predictions (17%) (1 epoch early: 6 segments, 2 epochs early: 2 segments), and 4 segments of 'delayed' predictions (8%) (1 epoch delayed: 3 segments, 2 epochs delayed: 1 segment). This result indicates that the trained SVM could detect (or even predict) the onset of drowsiness accurately in 45 out of the 49 EEG data segments up to 10-s time resolution.

4. Discussion

In this study, a well-defined distinguishing criterion was used, which followed closely with Hori's criterion of drowsiness detection to distinguish EEG alertness from drowsiness under simulated driving conditions (Hori et al., 1994). Epochs of the driving simulation period corresponding to normal fast eye blinks and EEG beta activity were classified as 'alert', and epochs corresponding to slower eye closures with dominant alpha activity and alpha dropout events were classified as 'drowsy'.(Hart, 1992; Doughty, 2002; Dinges et al., 1998; Santamaria and Chiappa, 1987). This manual classification was compared with the classification done by a SVM classifier trained to distinguish the 2 classes of EEG data by using 4 distinguishing frequency features on each of the delta, theta, alpha and beta bandwidths for each EEG channel.

The SVM results showed that the classification was highly successful in distinguishing EEG of normal wakefulness from light drowsiness, with an accuracy of over 99%. The trained SVM was also able to predict the same 'switching point' from alertness to drowsiness as identified by manual scoring within a 10-s epoch window in 75% of EEG segments. The SVM was able to give earlier predictions of the impending onset of drowsiness in 15% of EEG segments at 10-s time resolution. Since the SVM was to be developed as a fore-warning detector of drowsiness for driving safety, it could be deduced from the results that the SVM was able to predict the onset of drowsiness reliably and effectively. This means that the trained SVM could match the standards of manual classification and can therefore be used as an automatic detection method of drowsiness while driving.

It should be noted that although this study has produced promising results for SVM based automatic detection of drowsiness, there are a number of challenges that one needs to be aware of. The first is the consistency of the manual classification of EEG data. In this study, only data which were agreed upon by both raters as clear-cut examples of drowsiness and alertness was taken for analysis and ambiguous segments were discarded. Further testing and development is necessary to develop algorithms for the SVM system when EEG segments are ambiguous and unable to be correctly classified. The second is to consider widening the selection criteria of subjects in future studies of automatic detection of sleepiness whilst driving, since in this study subject selection was narrow with young healthy participants, It would be particularly important for future studies to include sleep disorders to be able to determine how SVM performance results may vary. In the present study, the sample population of subjects has been restricted to young healthy tertiary students 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. The third is with the number of EEG channels to be used. The high SVM classification accuracy established in this study may possibly be compromised if less EEG channels were used. This study employed a full 19-channel EEG recording system. However, if viewed from an economic or ergonomic aspect with respect to product development, a full set of EEG recording may not be feasible. Key EEG channel selection could be worthy of future investigations so that the optimal number of EEG channels can be determined.

Several studies have reported the feasibility of detecting operator drowsiness based on the EEG data in attention-sustained experiments and they used a fairly simple logic function, linear or nonlinear regression, or neural networks (Lal et al., 2003; Vuckovic et al., 2002; Wilson and Bracewell, 2000). For example, the algorithm developed by Lal et al. (2003) to detect driver fatigue used an algorithmic Boolean logic with predetermined thresholds to classify the alert and fatigue EEG. They reported a classification accuracy of around 90% in automatic classification of alert and fatigue states. The classification accuracy of around 99% obtained in the present study demonstrates the suitability of SVM for automatic detection of driver drowsiness.

A remarkable property of SVM is its good generalization capacity independent of the input space dimension (Cristianini and Shawe-Taylor, 2000). Even for the sparse learning problems where the ratio of the number of training data to the number of features is low, SVM generally can still give good performance in predicting unseen data with a moderate model selection effort (i.e. tuning of its hyper-parameters). This is particularly relevant to many biomedical problems, where one might often face such sparse learning problems. This could be due to the typical inherent redundancy of biomedical data (such as the multi-channel EEG data and the microarray data). Hence, SVM is a usable technique without having to know all detailed knowledge from the considered biomedical measures.

5. Conclusions

In this study, SVM has been used for automatic EEG detection of the onset of drowsiness while driving. The trained SVM program was tested on unclassified EEG data and subsequently checked for concordance with manual classification. The classification accuracy reached 99.3%. The SVM program was also able to predict the transition from alertness to drowsiness reliably in over 90% of data samples. This study shows that automatic analysis and detection of drowsiness EEG is possible by SVM and SVM is a good candidate for developing pre-emptive automatic drowsiness detection systems for driving safety.

Acknowledgement

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Appendix: Support vector machines algorithm

Given a dataset D consisting of N samples in the form of $\{\mathbf{x}_j, y_j\}_{j=1}^{N}$, where $\mathbf{x}_j \in R^d$ is the jth sample and $y_j \in \{1, 1\}$ is the corresponding class label, the basic principle of SVM for the two-class classification problem is to build an optimal separating hyperplane with largest margin between two classes. If the data are not linearly separable in the input space R^d (as most of the real-world problems), a nonlinear SVM is often used by mapping the feature vector $\mathbf{x} \in R^d$ into a high (possibly infinite) dimensional Euclidean space, H, using a nonlinear mapping function Φ: $R^d \rightarrow H$. This is motivated simply by the fact that data from two classes can always be separated by a hyperplane with an appropriate nonlinear mapping function Φ to a sufficiently high dimension (Duda et al., 2001). In the case of nonlinear SVM, the decision boundary of the two-class problems takes the form of an optimal separating hyperplane, $\mathbf{w} \cdot \Phi(\mathbf{x}) + b = 0$, in H, obtained by solving the convex optimization problem

$$\begin{aligned} &\min_{\mathbf{w},b,\xi} \quad \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{N}\xi_i, \\ &\text{s.t.} \quad y_i(\mathbf{w}\cdot\Phi(\mathbf{x}_i) + b) + \xi_i \geqslant 1 \text{ and } \xi_i \geqslant 0, \\ &\quad \text{for } i = 1, \cdots, N, \end{aligned} \tag{A}$$

over $\mathbf{w} \in H$, $b \in R$ and the non-negative slack variable $\xi \in R^N$. In the above, C is a parameter that balances the size of $\mathbf{w}$ and the sum of ξ_i. It is well known that the numerical computation of Eq. (A) is achieved through its dual formulation. Suppose α_i be the Lagrange multiplier corresponding to the ith inequality, then the dual of (A) can be shown to be

$$\begin{aligned} &\min_{\alpha} \quad \frac{1}{2}\sum_{i,j=1}^{N} y_i y_j \alpha_i \alpha_j K(\mathbf{x}_i, \mathbf{x}_j) - \sum_{i=1}^{N}\alpha_i, \\ &\text{s.t.} \quad \sum_{i=1}^{N} y_i\alpha_i = 0 \text{ and } 0 \leqslant \alpha_i \leqslant C, \quad \text{for } i = 1, \cdots, N, \end{aligned} \tag{B}$$

where the kernel function $K(\mathbf{x}_i,\mathbf{x}_j) = \Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x}_j)$ and

$$\mathbf{w} = \sum_{i=1}^{N} \alpha_i y_i \Phi(\mathbf{x}_i). \tag{C}$$

With (C), the expression of the hyperplane $\mathbf{w} \cdot \Phi(\mathbf{x}) + b = 0$ becomes

$$f(\mathbf{x}) = \sum_{i=1}^{N} y_i \alpha_i K(\mathbf{x}_i, \mathbf{x}) + b \tag{D}$$

and serves as the decision function for all unseen samples $\mathbf{x}$ in that the predicted class is +1 if $f(\mathbf{x}) > 0$ and 1 otherwise.

For the reliable detection of drowsiness, a nonlinear SVM is used in this study with the popular Gaussian kernel

$$K(\mathbf{x}_k, \mathbf{x}_j) = \exp(-\gamma\|\mathbf{x}_k - \mathbf{x}_j\|^2), \tag{E}$$

where γ is the kernel parameter. It is fair to note that the parameters C and γ should be tuned properly for accurate prediction of unseen samples. In this study, they were selected using LIBSVM (Chang and Lin, 2001) by 5-fold cross-validation over the following grid of (C, γ): $[2^{-7}, \ldots, 2^7] \times [2^{-10}, \ldots, 2^3]$.

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