An EEG-based Perceptual Function Integration Network for Application to Drowsy Driving

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Abstract

Drowsy driving is among the most critical causes of fatal crashes. Thus, the development of an effective algorithm for detecting a driver's cognitive state demands immediate attention. For decades, studies have observed clear evidence using electroencephalography that the brain's rhythmic activities fluctuate from alertness to drowsiness. Recognition of this physiological signal is the major consideration of neural engineering for designing a feasible countermeasure. This study proposed a perceptual function integration system which used spectral features from multiple independent brain sources for application to recognize the driver's vigilance state. The analysis of brain spectral dynamics demonstrated physiological evidenced that the activities of the multiple cortical sources were highly related to the changes of the vigilance state. The system performances showed a robust and improved accuracy as much as 88% higher than any of results performed by a single-source approach.

Keywords: Electroencephalogram, Independent Component Analysis, Multiple Classifiers System, Drowsy Driving

1. Introduction

Driving performance is often reduced, especially during long-term, monotonous, or nighttime driving. Drowsiness is assumed to be a major factor in the failure of drivers to avoid accidents and leads to many collisions, injuries, and fatalities each year (Vaca, Harris, Garrison, & McKay, 2005). Accordingly, developing an effective learning algorithm for detecting drowsiness and providing feedback through a warning is an urgent necessity for real-life driving.

A number of bio-behavioral features, such as eye blinking (Caffier, Erdmann, & Ullsperger, 2003) and head nodding, have been developed to monitor the drowsiness. However, false alarms are likely to occur since these facial attributes are not always accompanied by the drowsy state (Horne & Reyner, 1999). Over the past few decades, electroencephalography (EEG), the electric current produced by the activity of the brain, has been proven to be a robust physiological indicator for assessing vigilance states (Lal & Craig, 2001, 2002; Makeig & Jung, 1996). Numerous literatures of the EEG study suggest that delta (1-3 Hz), theta (4-7 Hz), and alpha (8-12 Hz) waves are highly correlated with fatigue, drowsiness, and poor task performance (Makeig, Jung, & Sejnowski, 2000; Papadelis, *et al.*, 2007; Schier, 2000). The investigators have further applied statistic or machine-learning algorithms to characterize the EEG features toward real-life applications such as lapse detection (Davidson, Jones, & Peiris, 2007), fatigue monitor (Jap, Lal, Fischer, & Bekiaris, 2009; Lal, Craig, Boord, Kirkup, & Nguyen, 2003), alertness evaluation (Jung, Makeig, Stensmo, & Sejnowski, 1997), or accident prevention (Papadelis, *et al.*, 2007). However, the scalp EEG recording is considered as a weighted linear mixture of brain sources, non-brain sources, and artifacts due to volume conduction (Jung*, et al.*, 2001; Onton & Makeig, 2006). Even in perfect laboratory conditions, the artifacts, such as body and eye movements, are known to strongly influence the EEG recordings. Hence, the spectral oscillations of the channel-based recordings might not purely correlate with the cognitive state.

The independent component analysis (ICA)(Hyvärinen, Karhunen, & Oja, 2001; Hyvarinen & Oja, 2000), as well as generalized singular-value decomposition (Harner, 1990; Liu, de Zwart, van Gelderen, Kuo, & Duyn, 2012) and blind source separation (Cardoso, 1998; Fitzgibbon, Powers, Pope, & Clark, 2007; Parra & Sajda, 2003), have been widely adopted to deal with the problem of artifact removal. Multichannel EEG signals are decomposed into maximally independent and spatially fixed components (ICs) (Castellanos & Makarov, 2006; Jung*, et al.*, 2000; Makeig, Jung, Bell, Ghahremani, & Sejnowski, 1997). Analysis of spectral dynamics have revealed that the independent sources (non-artifact sources) are able to obtain a more distinct correlation with cognitive states than scalp EEG activities (Jung*, et al.*, 2001; Onton & Makeig, 2006). Our previous work (Lin*, et al.*, 2006) further demonstrated the feasibility of using occipital components to predict lapses in driving behaviors. However, several points can be further addressed and improved. First, a drowsy driver might fail to functionally engage multi-perceptual functions (Groeger, 2000), such as attention, decision making, visual processing, and sensorimotor coordination, resulting in a series of dangerous driving behaviors with a sluggish reaction time in response to traffic events. The coherence and interaction between distinct brain sources intuitively appear to be important. However, a subject-dependent feature-extraction approach will limit the feasibility of a drowsy-driving alert system for public use. Some extracted components can be present in recordings from one subject but not in the other. Each individual is intended to be re-analyzed so that an individual's specific brain processing is associated with the driving task. To the best our knowledge, no study has yet been performed that explores subject-independent brain sources as biomarkers for addressing the classification of driving performance.

To gain insight into the EEG-based drowsy-driving alert system, the objective of this study is twofold. First, this study implemented ICA to extract underlying brain sources engaging in a simulated-driving task. Second, this study further explored an optimal framework based on the resultant common brain processing with a nonparametric feature extraction for improving classification performance. The contribution of this study is the introduction of an EEG-based perceptual function integration network for characterizing and classifying driving performance by drawing on the emerging framework of neuroscience and computer science.

2. EEG-based Perceptual Function Integration Network

Figure 1 shows the schematic diagram of the proposed system. The design aimed to fuse the information from multiple (available) independent sources to predict the vigilance state of drivers. The short-term and long-term segments of EEG time series were transformed into the power spectrum and then concatenated together to represent brain activity patterns. In the machine learning stage, informative features for each source were extracted to build a multiple classifier system. The details are introduced in the following sections.

2.1.Layer I: Brain independent sources

For the purpose of recovering the underlying sources from mixed signals, an independent component analysis (ICA) was applied as the connector between EEG signals and brain sources. Based on the linear form of ICA, the time courses of n-channel EEG signals, $\boldsymbol{X} = [\ X_1\ X_2 \ldots X_n\ ]$, are linearly separated into mutually independent components:

$$\boldsymbol{U}^{\mathrm{T}} = \boldsymbol{M}_{n\times n} \times \boldsymbol{X}^{\mathrm{T}}, \tag{1}$$

where $\boldsymbol{U} = [U_1\ U_2\ \ldots\ U_n]$. The unmixing matrix $\boldsymbol{M}$ was implemented by extended infomax ICA (Jung*, et al.*, 1998; Lee, Girolami, & Sejnowski., 1999) as follows:

$$\triangle\boldsymbol{M} = \boldsymbol{M}^{-1} + (\boldsymbol{I} - 2\boldsymbol{U}\boldsymbol{X}^{\mathrm{T}}). \tag{2}$$

We then performed the back projection (Delorme & Makeig, 2004) of independent sources on EEG signals to distinguish brain sources from artificial signals as the following:

$$\boldsymbol{\Gamma} \times \begin{bmatrix} U_1 \\ U_2 \\ \vdots \\ U_n \end{bmatrix} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_n \end{bmatrix}, \tag{3}$$

where the column of $\boldsymbol{\Gamma}$, the inverse matrix of $\boldsymbol{M}$, indicating the projection strengths of each independent process to the scalp sensors, was rendered as a 2-D scalp topography as shown in Fig. 2.

According to previous studies related to drowsiness, fatigue, and poor performance (Huang, Jung, Delorme, & Makeig, 2008; Huang, Jung, & Makeig, 2009), the scalp maps with high projection strengths distributed around the frontal, central, somatomotor, parietal, and occipital cortices were selected as the components of interest, while eye-related noises, line noises, and other non-brain activities were discarded. The automatic artifact identification and the component clustering was done by ADJUST (Mognon, Jovicich, Bruzzone, & Buiatti, 2011) and STUDY (Delorme & Makeig, 2004).

The term, U_i, is assumed to be one of the time courses of brain-independent sources. The corresponding *i*-th row $\boldsymbol{M}$ of Eq. (1) is preserved as the connection strengths between input layer and layer I. The *i*-th node of layer I is represented as the linear sum of the product of the connection weights and the EEG signals as the following:

$$U_i = [m_{i1}\ m_{i2}\ \ldots m_{in}] \times \boldsymbol{X} = \sum_{\ell=1}^{n} m_{i\ell} X_\ell. \tag{4}$$

2.2.Layer II: Power spectrum estimated by FFT

In layer II, a time series of the brain-independent process, U_i, was transformed into a frequency domain using fast Fourier transform (FFT) to characterize the spectral dynamics of brain rhythms. The node of v_{ji} representing the logarithmic spectral power of the *i*-th brain process on f_j Hz was calculated as the following:

$$v_{ji} = 10 \cdot \log\left(\left|\sum_{\ell=0}^{250-1} u_{i\ell} \cdot e^{-\mathbf{i}\frac{2\pi f_j \ell}{250}}\right|^2\right), \tag{5}$$

where i is the imaginary unit and $j = 1, 2, \ldots, p$. In this study, the resultant power spectrum consists of thirty frequency bins from 0.98 Hz to 30.3 Hz with a frequency resolution near 1 Hz, i.e., $f_j \in [0.98, 30.3]$. Then, the power spectral array of the global and local EEG segments was concatenated to form a larger feature dimension ($p = 60$) for further analysis.

2.3.Layer III: Driving-related EEG features extraction

The current layer aimed at extracting driving-related spectral features from $\mathbb{R}^p$ into $\mathbb{R}^{p'}$ (also called feature extraction or dimension reduction). Given a transformation matrix $\boldsymbol{A}_i \in \mathbb{R}^{p \times p'}$ for the i-th brain process, a linear space transformation was performed on $V_i \in \mathbb{R}^p$ such that

$$\begin{aligned} W_i &= \boldsymbol{A}_i^{\mathrm{T}} \times V_i \\ &= \begin{bmatrix} a_{11}^{(i)} & \dots & a_{1j}^{(i)} & \dots & a_{1p}^{(i)} \\ \vdots & & \ddots & & \vdots \\ a_{k1}^{(i)} & \dots & a_{kj}^{(i)} & \dots & a_{kp}^{(i)} \\ \vdots & & \ddots & & \vdots \\ a_{p'1}^{(i)} & \dots & a_{p'j}^{(i)} & \dots & a_{p'p}^{(i)} \end{bmatrix}_{p' \times p} \times V_i, \end{aligned} \tag{6}$$

where W_i is the driving-related spectrum with a lower dimensionality $p' \leq p$. The k-th row (the node of the layer III) of W_i is as the following:

$$w_{ki} = \sum_{\ell=1}^{p} a_{k\ell}^{(i)} \times v_{\ell i}, \tag{7}$$

where $k = 1, 2, \dots, p'$.

In terms of the assessment of $\boldsymbol{A}$, several well-known algorithms, including sequential forward selection (SFS)(Jain, 1997), principal component analysis (PCA)(Fukunaga, 1990), regularized linear discriminate analysis (LDA)(Fukunaga, 1990) and nonparametric weighted feature extraction (NWFE)(Kuo & Landgrebe, 2004) were applied for the comparison of classification performances.

For reducing the loading of computation, the most expressive feature (the best single feature that guarantees the optimal subset or the eigenvector with the largest eigenvalue) was used at the next step. Additionally, the loading value (Esbensen, Guyot, Westad, & Houmøller, 2002) is a common estimator to indicate the major contributor of the original variables participating in defining the new features. To verify the consistency between fundamental results and the machine learning, the loading values of the k-th extracted spectrum were analyzed as follows:

$$\phi_{kj} = \left| \frac{a_{kj} \times \sqrt{\lambda_k}}{s_j} \right|, \tag{8}$$

where λ_k and s_j are the standard deviation of $\boldsymbol{W}$ at the *k*-th feature and $\boldsymbol{V}$ at the *j*-th frequency bin, respectively.

2.4.Layer IV: Brain source classifiers

Each node of Layer IV is a single classifier established from distinct brain sources. The driving-related spectrum $\boldsymbol{W}_i$ accompanying class labels $\boldsymbol{Y}_i$ was used as the training data pair to train the parameters of the base classifier $C_i \in \boldsymbol{C}$, where $i = 1, 2, \ldots, d$. The commonly used algorithms Gaussian classifier (GC)(Fukunaga, 1990), support vector machine (SVM)(Vapnik, 1998), and radial basis function neural network (RBFNN) (Bishop, 1996) were implemented in the proposed model.

2.5.Layer V: Decision fusion

As shown in Fig. 3, all of the outputs $o_i = \{1, 2, \ldots, L\}$ derived from C_i were integrated in Layer V. The operator of the fusion method was the majority voting as shown in Eq. (9) to obtain the final result of the driving performance:

$$\overline{\boldsymbol{O}} = \underset{\ell \in \{1,2,\ldots,L\}}{\text{argmax}}\ card(i \mid o_i = \ell, i = 1, 2, \ldots, d), \tag{9}$$

where $card(\cdot)$ denotes the cardinality of the set and L denotes the number of the category.

3. Environment and Material

3.1 Virtual-reality based driving environment and experimental paradigm

In the previous study (Lin*, et al.*, 2007), we constructed a virtual-reality (VR)-based high-fidelity realistic driving environment. The synchronized scenes were projected from six projectors to constitute a surrounding 360° vision. At the center of the projected scenes, we mounted a real vehicle on a six degree-of-freedom motion platform (Fig. 4A). A four-lane highway scene projected on a surrounding screen simulates a visually monotonous and unexciting stimulus of a driving condition to induce drowsiness (Fig. 4B), and the refresh rate of the highway scene was set properly to emulate a car driving at a fixed speed of 100 km/hr.

An event-related land-departure paradigm (Fig. 4C)(Huang, *et al.*, 2009) was implemented in a VR driving simulator. This experimental paradigm mimics a nonideal road surface to make the car randomly drift out of the cruising lane (deviation onset) at a deviation speed (S_d) of 5 km/hr toward the right or left side. The participant was instructed to steer the car (response onset) back to the center of the original lane (response offset) as soon as possible when encountering each deviation event. During the 1.5hr long experiment, the reaction time (RT, the duration between the deviation onset and the response onset) was recorded and used to label the vigilance state for each of the experiment trials.

3.2 Vigilance states

The short-term and long-term of RT is introduced here to categorize the collected EEG trials into distinct groups of the vigilance state. The *local* RT $(\mathbf{RT}_l)$ is the duration between the deviation onset and response onset, as defined in (Huang, *et al.*, 2009), to evaluate the instant response to the current lane-departure. The *global* RT $(\mathbf{RT}_g)$, an average $\mathbf{RT}_l$ of the trials within the preceding or following windows, evaluates the long-term transition of the vigilance state. For example, the $\mathbf{RT}_g$ of the t-th trial can be calculated as the following:

$$\mathbf{RT}_g(t) = \sum_{k=t-w}^{t+w} \frac{\mathbf{RT}_l(k)}{2w+1}, \tag{10}$$

where w was set to two in this study.

As the distribution of $\mathbf{RT}_l$-$\mathbf{RT}_g$ shown in Fig. 5, the t-th trial could be assigned into five classes of vigilance states as follows:

$$\mathbf{trial}(t) \in \begin{cases} \mathbf{A} & \text{for } \{\mathbf{RT}_l(t) \le 0.7\} \cap \{\mathbf{RT}_g(t) \le 0.7\} \\ \mathbf{C} & \text{for } \{\mathbf{RT}_l(t) \ge 2.1\} \cap \{\mathbf{RT}_g(t) \le 2.1\} \\ \mathbf{D} & \text{for } \{\mathbf{RT}_l(t) \ge 2.1\} \cap \{\mathbf{RT}_g(t) \ge 2.1\}, \\ \mathbf{E} & \text{for } \{\mathbf{RT}_l(t) \le 2.1\} \cap \{\mathbf{RT}_g(t) \ge 2.1\} \\ \mathbf{B} & \text{otherwise} \end{cases} \tag{11}$$

where the cluster $\mathbf{A}$ and the cluster $\mathbf{D}$ locating on the diagonal $(\mathbf{RT}_l \approxeq \mathbf{RT}_g)$, represent alertness and drowsiness, respectively. The cluster $\mathbf{C}$ $(\mathbf{RT}_l > \mathbf{RT}_g)$ represents the inattention episodes in which the subject momentarily distracted attention from the driving task, resulting in $\mathbf{RT}_l$ being slower than $\mathbf{RT}_g$. The cluster $\mathbf{E}$ $(\mathbf{RT}_l < \mathbf{RT}_g)$ is the abrupt-awaking case that a drowsy subject $(\mathbf{RT}_g \ge 2.1)$ was suddenly roused by perceiving the motion cue and responded rapidly to the current trial; nevertheless, the subject still fell asleep on the next trials. The trials of cluster $\mathbf{B}$ were omitted since the transition state showed a large variability of behaviors between subjects. Therefore, the present study will demonstrate the feasibility of the proposed model for the four-class recognition problem.

3.3 Subject and EEG data acquisition

Ten volunteer subjects with normal or corrected to normal vision participated in the driving experiment. None of them had a history of psychiatric or sleep disorders. For EEG data acquisition, a Scan NuAmps Express system (Compumedics USA Inc., Charlotte, NC) recorded 30-channel EEG signals with a 16-bit quantization level at a sampling rate of 500 Hz by Ag/AgCl electrodes.

These electrodes were arranged on a quick-cap (Fig. 4C) according to a modified international 10-20 system (Homan, Herman, & Purdy, 1987). The impedance of all of the electrodes was maintained below 5kΩ. Prior to data analysis, the data was down-sampled to 250Hz and filtered with a band-pass FIR filter (1-50 Hz) to remove noises. For the *t*-th trial, 1-s baseline EEG data prior to the deviation onset (the *local* EEG segment) and the EEG segment taking from both preceding and following signals within the time window as Eq. (10)(the *global* EEG segment) were both extracted to link to the RT.

4. Environmental Results

In this study, the signals processing and the learning algorithms were implemented by using EEGLAB (Delorme & Makeig, 2004), PRTools (Heijden, Duin, Ridder, & Tax, 2004), and LIBSVM (Chang & Lin, 2011). For validating the performance of the proposed model, a leave-one-subject-out cross-validation process (Esterman, Tamber-Rosenau, Chiu, & Yantis, 2010) using the samples from single subject as the validation data and the samples from the remaining subject as the training data was repeated for all ten subjects. As listed in Table 1, the number of extracted components is inconsistent between subjects that only six subjects (s01, s02, s05, s07, s08, s10) fulfilled the requirement of full model; and moreover, some regions of interest are represented in more than one component within an individual. Thus, the spectral powers of these repeated components were combined by simple averaging method. For the case of reduced models (s03, s04, s06, s09), the available components were voters for the final decision. If no category had the support of a majority of votes, a random process was used to choose one of the vigilance states.

4.1 EEG power dynamics

Figures 6A shows the relationship between the spectral powers and the RTs for the frontal, central, somatomotor, parietal, and occipital components, respectively. Clearly, the power (in dB) exhibited an increasing trend as the RT increased, particularly over the low frequency range (< 12 Hz). The blue line and the red line represent the averages of the power spectra for the alert and the drowsy state, respectively. A significant test at the significance level of 5% performed the comparison of two groups and showed that the powers of the drowsy group were significantly higher than that of the alert group over the frequency range of 1-12 Hz across five brain sources. However, significant differences in beta range (20-30 Hz) only occurred at the central and somatomotor sources.

The comparison of spectral powers between the alertness and drowsiness groups (Fig. 6B) demonstrated that the extent of the four rhythms associated with the changes in the vigilance state. The results show that the frontal, central, and somatomotor regions are dominated by delta and theta rhythms, whereas the parietal and occipital regions are dominated by delta, theta, and alpha rhythms.

4.2 Classification results

Table 2 lists the comparison of the classification results using GC, SVM, and RBFNN between four types of features ($p' = 1$). Note that the number of extracted feature was set to one in this study for reducing the computational complexity. The highlighted cells indicate the best accuracy of each source among all of the combinations of learning algorithms, and the numbers in bold represent the highest accuracy obtained among brain sources while using the same feature extraction and classifier. The classification result of the proposed model is shown in the last column of Table 2, in which a note is attached to represent a significant improvement (*: $p < 0.05$ or **: $p < 0.01$) compared to the highest accuracy (in bold). The following are noteworthy findings. First, classification performances obtained with additional feature extractions were evidently better than those without feature extractions (using the original spectral array) with an improvement of 6-15%. Second, using the nonparametric EEG features can yield the best accuracy (highlighted), ranging from 80% to 84% for different sources, especially in the cases that used SVM. Third, when comparing the classification results among individual sources, the parietal source generally achieved the best classification accuracy (in bold). Last, the proposed component system successively improved the classification accuracy to 88% (with significant difference) compared to those results obtained using an individual source.

5. Discussion

5.1 Drowsiness-related EEG spectral features

Driving is a complex task in daily living that involves selective attention, planning, decision making, motor skills, spatial orientation, sensory integration, visual reception, and object recognition (Groeger, 2000). This study employed ICA (Jung, *et al.*, 2001; Onton & Makeig, 2006; Onton, Westerfield, Townsend, & Makeig, 2006) on EEG signals to recover the underlying regions of the brain and assess the brain rhythmic activities in the changes of the vigilance state. Moreover, we adopt multiple-source approaches to extract the most informative EEG features for the efficiency of classification work. The followings are detail discussions of the relationships between physiological functions and the cortical region involved in the driving task.

The frontal component is located near the anterior cingulate cortex and the prefrontal cortex (Broadmann areas 32 and 9). This area serves as a typical region for performing executive functions, attention, and decision making (Gazzaniga, Ivry, & Mangun, 2008; Jones & Harrison, 2001). The significantly increasing powers of delta and theta rhythms in the condition of poor performance (Fig. 6 A) are consistent with previous studies in cases of reduced levels of attention (Makeig*, et al.*, 2000), severe driving errors (Papadelis*, et al.*, 2007), sleep-deprived driving (Eoh, Chung, & Kim, 2005), and even attention-related disorder (Hermens*, et al.*, 2005). Additionally, many existing studies have indicated that drowsiness, fatigue, and sleep deprivation are important factors that impair motor performance in terms of the reaction time and the accuracy (Baulk, Reyner, & Horne, 2001; Williamson & Feyer, 2000). The central and somatomotor components locating near the motor and sensory cortices (Broadmann areas 1-6) are implicated in the motor control and the sensation (Gazzaniga*, et al.*, 2008). This area, the region of optimal electrode placement, is usually used for the design of motion-imagery BCI (Blankertz, Curio, & Müller, 2002). Results shown in Fig. 6 (B) and (C) reinforce the physiological evidence of increases in EEG power (1-12 Hz) in correlation with poor motor performance (Baulk*, et al.*, 2001; Papadelis*, et al.*, 2007). In addition, the central and somatomotor components showed significant differences between the alert state and the drowsy state at 20-30 Hz. This event-related synchronization and desynchronization of the beta power usually implicates the sensorimotor activation and deactivation (Neuper, Wörtz, &

Pfurtscheller, 2006). The present result demonstrated a strong rebound of the beta power in the drowsy state following action termination, which is consistent with previous studies (Huang*, et al.*, 2008; Jurkiewicz, Gaetz, Bostan, & Cheyne, 2006).

Parietal and occipital components are located near the posterior cingulate cortex (Broadmann areas 23 and 31) and the occipital cortex (Broadmann areas 18-20), respectively. These areas are involved with the integration of sensory information and with visual reception (Gazzaniga*, et al.*, 2008). The visuospatial processing flow plays an important indicator of the attention level (Worden, Foxe, Wang, & Simpson, 2000) and the drowsiness level (Huang*, et al.*, 2009). Increasing power in delta, theta, and alpha rhythms are usually related to poor task performance, fatigue, or drowsiness (Davidson*, et al.*, 2007; Jap*, et al.*, 2009; Lal & Craig, 2001, 2002; Lal*, et al.*, 2003; Makeig & Jung, 1996; Makeig*, et al.*, 2000; Papadelis*, et al.*, 2007; Schier, 2000; Torsvall & åAkerstedt, 1987).

5.2 Perceptual Function Integration Network

The 30-channel EEG signals were initially decomposed into independent sources of five components of interest using ICA. Compared to the existing studies that detected lapse and drowsiness based on time lines of EEG signals at a few scalp sites (Lal & Craig, 2001), the ICA signal of the brain source was associated with a unique projecting topography allowed the classification system to reduce the effects of artifacts. This is a practical solution for application, which often involves a wide variety of artifacts from the extrinsic environment that may influence EEG acquisition. In addition, compared to our previous studies (Lin*, et al.*, 2007; Lin, Wu, Jung, Liang, & Huang, 2005), which developed a subject-dependent algorithm, an integration system based on multiple independent sources provides a subject-independent solution for detecting a driver’s vigilance state. One of the important contributions of this work is that the proposed model could work even though only one of the components of interest was extracted after the ICA processing. However, some ICs can be present in recordings from one subject but not in the other. One of the solution is to use the group ICA method (Calhoun, *et al.*, 2001; Schmithorst & Holland, 2004), in which statistics are performed for a component over subjects and sessions. Although ADJUST (Mognon, *et al.*, 2011) and STUDY (Delorme & Makeig, 2004) are able to automatically identify artifacts and cluster the components, an automatic selection of components of interest still needs to be developed in the future.

In terms of the feature extraction, the reduced dimensionality (extracted from only one feature in this study) not only profits from a reduction of the complexity of the classifier training but also preserves the informative spectra. However, because of the restriction of unsupervised learning, the PCA-based features with the maximum variability are unable to describe the attributes between the vigilance groups that result in unsatisfactory findings. Even though LDA-based and nonparametric features are both based on Fisher’s criterion, nonparametric approaches invariably obtain the best accuracy among different sources. This result ascribes its success to the regularized form to the problem of a within-scatter matrix for small sample sizes and the nonparametric weighted approach to enlarge the discriminability of boundary patterns.

According to the classification results, the parietal source generally obtains the best accuracy among various cases, and the next-best accuracy occurs at the occipital source. From the perspective of machine learning, this result supports that the drowsiness mostly impairs the sensory integration and the visual reception, which are executed by the parietal and occipital cortices, respectively. In terms of the classifiers, SVM, as previously reported (Yeo, Li, Shen, & Wilder-Smith, 2009), is able to overcome small sample size data with a relatively high dimensionality (in the case of using all of the original spectrum). However, GC and RBFNN suffer from a small sample size and thus obtain an unsatisfactory result. Nevertheless, the classification accuracy of these two classifiers accompanying feature extraction is comparable to that of SVM.

The outputs derived from the different classifiers are combined by the majority-voting rule to obtain the final decision of the vigilance state. The idea of the integration model originates from the concept of the multiple classifier system, which has superior statistical, computational, and representational aspects that convinces the proposed model to obtain a more accurate result than a single classifier performs (Dietterich, 2000). The results in Table 2 show an evidential improvement in the classification accuracy and small deviation, which supports the design of integrating the information derived from different brain regions to reach a better decision. Although the transition state was omitted in this study, the posterior probability obtained from the classification result can be used for evaluating the class-membership of the EEG input to one of the drowsiness levels (Rosipal, *et al.*, 2007).

5.3 Nonparametric EEG features

The loading plot (Fig. 8) demonstrates the major contributor of the frequency participating in defining informative features. The estimator is referred to Eq. (8).

For SFS-based features, frequency bins are selected based on delta rhythms at the anterior brain region (Figs. 8A, 8B, and 8C) and theta rhythms at the posterior brain region (Figs. 8C and 8D), which is consistent with the fundamental findings shown in Fig. 6C. For the nonparametric approach, the extracted features are the weighted sum of the original frequencies, which show a smoothing distribution of the loading plot similar to the finding in Fig. 6C cross five sources. Table 3 provides the correlation coefficients of the distributions between those shown in Fig. 8 and Fig. 6C. The positive value is the desired outcome, which suggests a higher similarity between these two distributions. The high positive correlation (0.780-0.944) for the nonparametric feature indicates a good description of the extracted feature to characterize the main differences between alert and drowsy EEG patterns. However, PCA-based and LDA-based features show low positive correlations or even negative correlations with Fig. 6, which is a possible explanation for obtaining a lower accuracy.

In summary, the physiological evidence of brain dynamics confirms that a large cortical region spanning frontal, central, somatomotor, parietal, and occipital areas is involved in the changes of vigilance states. The dynamics of delta, theta, and alpha rhythms may be used as an indicator to explain the functional state of attention, motor, visual cortical systems. This appears to be a reasonable approach to integrate the informative features from different brain sources for vigilance state recognition. Moreover, the best performance could be obtained by using nonparametric features to perfectly extract EEG signatures.

One of the major bottle-neck of the proposed algorithm to achieve 88% of accuracy is the effectiveness of EEG artifact removal. The classification performance of the system and the ICA algorithm becomes degraded and unstable if the collected EEG signals are severely distorted by artifacts. Hence, an online algorithm for artifact removal and signal reconstruction is necessary before the ICA application. We would like to integrate this technique with the proposed algorithm to improve the system performance in the future works.

6. Conclusion

In this study, the proposed integration network was designed based on the ideal of the multiple classifier system to integrate different brain sources for the vigilance state classification. This system contained five base classifiers trained from five brain sources that had different physiological characteristics and meanings in response to the changes of the driving performance and the cognitive state. The model could work even though only one of the components of interest was extracted after the ICA processing. The experimental results showed that the parietal source classifier obtained the best accuracy among the five components of interest, and further, the proposed model outperformed the conventional signal-based classifier. Our results suggested that the underlying brain sources of multiple cortices were informative in characterizing the vigilance state of the driver, and the classification system with the nonparametric feature extraction was a practical approach to strengthening the reliability and practicality for detecting vigilance states.

Acknowledgements

This work was supported in part by the Aiming for the Top University Plan of National Chiao Tung University, the Ministry of Education, Taiwan, under Contract 103W963, and in part by UST-UCSD International Center of Excellence in Advanced Bioengineering sponsored by the Ministry of Science and Technology I-RiCE Program under Grant Number: NSC-102-2911-I-009-101. Research was sponsored by the Army Research Laboratory and was accomplished under Cooperative Agreement Number W911NF-10-2-0022. The views and the conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the Army Research Laboratory or the U.S Government. The U.S Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation herein.

Figure legend

Fig. 1. The schematic diagram of the EEG-based perceptual function integration network. The proposed classification model is based on the integration of EEG features extracted from multiple independent sources to recognize driving performance.

Fig. 2. Scalp topography of the inverse of the unmixing matrix. Left panel: six components of interest are the frontal, central, somatomotor, parietal, and occipital components. Right panel: components of non-interest, such as eye-related noises, line noises, and other non-brain activities. The automatic artifact identification and the component clustering was implemented by ADJUST (Mognon*, et al.*, 2011) and STUDY (Delorme & Makeig, 2004).

Fig. 3. (A) EEG-based perceptual function integration network. Layer I: brain-independent source, Layer II: power spectrum, Layer III: driving-related spectrum, Layer IV: brain source classifier, and Layer V: decision fusion. The connections between layers use independent component analysis, fast Fourier transform, nonparametric EEG feature extraction, classifier, and fusion method. (B) The structure of the proposed algorithm.

Fig. 4. The simulated driving environment and the schematic diagram of the experimental paradigm. (A) The driving simulator was mounted on a motion platform. (B) The VR scene simulates nighttime cruising at a speed of 100 km/hr on a four-lane highway without other traffic. (C) The event-related lane-departure paradigm. Deviation onset: the time when the car starts to drift to the right or left of the cruising lane; Response onset: the time when subjects use the steering wheel; Response offset: the time when the car returns to the original lane.

Fig. 5. The distribution of all trials with the local RT as the horizontal axis and the global RT as the vertical axis. The characters A to E represent the five types of vigilance states: A: alertness (high-performance driving), B: transition, C: alertness but inattention, D: drowsiness (low-performance driving), and E: drowsiness but abrupt-awake. The two dotted lines located at 0.7 s and 2.1 s represent the upper bound and the lower bound of A and D, respectively.

Fig. 6. (A) Moving-average power spectral changes of frontal, central, somatomotor, parietal, and occipital components (from left to right) sorted from fastest RT to slowest RT. The window size and step size are 10% of the trial number and one, respectively. (B) The comparison of spectral powers between alertness (blue trace) and drowsiness (red trace)(Wilcoxon signed rank test, $p <$ 0.05). (C) The difference in spectral power between alert and drowsy groups.

Fig. 7. Equivalent dipole source localization of five independent components. (A) Sagittal plane, (B) horizontal plane, and (C) coronal plane. Each independent component is in a different color, and the average position is labeled with a larger marker. Blue: frontal; yellow: central; green: somatomotor;

and red: occipital component. Each coherent activity across a small patch of cortex has a projection map on the scalp near the brain dipole (source), given a scalp map (shown in Fig. 4), a 3D-equivalent brain dipole was inferred by the DIPFIT function of the EEGLAB software (Delorme & Makeig, 2004) to locate the partial synchrony of local field potential processes in a brain lobe, cortex, or Broadmann area (Delorme & Makeig, 2004; Onton*, et al.*, 2006).

Fig. 8. The 1-D loading plots of the SFS, PCA, LDA, and nonparametric features. The panels, from top to bottom, are (A) frontal, (B) central, (C) somatomotor, (D) parietal, and (E) occipital sources. The x-axis is with delta (δ, 1~3 Hz), theta (θ, 4~7 Hz), alpha (α, 8~12 Hz), and beta (β, 13~30 Hz), and the y-axis is the loading value estimated by Eq. (21). The loading plot demonstrates the major contributor of the brain rhythms participating in defining informative features.

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