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Can arousing feedback rectify lapses in driving? Prediction from EEG power spectra

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Abstract

Objective. This study explores the neurophysiological changes, measured using an electroencephalogram (EEG), in response to an arousing warning signal delivered to drowsy drivers, and predicts the efficacy of the feedback based on changes in the EEG. *Approach.* Eleven healthy subjects participated in sustained-attention driving experiments. The driving task required participants to maintain their cruising position and compensate for randomly induced lane deviations using the steering wheel, while their EEG and driving performance were continuously monitored. The arousing warning signal was delivered to participants who experienced momentary behavioral lapses, failing to respond rapidly to lane-departure events (specifically the reaction time exceeded three times the alert reaction time). *Main results.* The results of our previous studies revealed that arousing feedback immediately reversed deteriorating driving performance, which was accompanied by concurrent EEG theta- and alpha-power suppression in the bilateral occipital areas. This study further proposes a feedback efficacy assessment system to accurately estimate the efficacy of arousing warning signals delivered to drowsy participants by monitoring the changes in their EEG power spectra immediately thereafter. The classification accuracy was up 77.8% for determining the need for triggering additional warning signals. *Significance.* The findings of this study, in conjunction with previous studies on EEG correlates of behavioral lapses, might lead to a practical closed-loop system to predict, monitor and rectify behavioral lapses of human operators in attention-critical settings.

(Some figures may appear in colour only in the online journal)

1. Introduction

Fatigue (or drowsiness) has been widely identified as a major problem in safety-critical work situations as well as in traffic (Fairclough and Graham 1999, Sexton *et al* 2000, Hanowski *et al* 2003). Although the causes of fatal traffic accidents are difficult to assess reliably, many studies (Vaca *et al* 2005, Landrigan 2008) have indicated that drowsiness is a primary contributing cause. The early detection of drivers' drowsiness, which often increases the likelihood of behavioral lapses, to maintain their cognitive capability and thereby prevent accidents is thus highly desired. The development of a means of detecting human fatigue or behavioral lapse to prevent further growth in the number of fatalities caused by traffic accidents, has increasingly attracted the attention of transportation safety administration, industry and the scientific community. Many studies have exploited various methods for measuring physiological changes, such as changes in blinking rate (Caffier *et al* 2003) and heart rate (Chua *et al* 2012) as a means of evaluating human cognitive capability.

Many studies (Makeig and Inlow 1993, Campagne *et al* 2004, Makeig and Jung 1996, Jung *et al* 1997, Lal and Craig 2002, Horne and Baulk 2004, Pastor *et al* 2006, Huang *et al* 2008, 2009, Lin *et al* 2010, Jap *et al* 2011) have also demonstrated that fluctuations in the behavioral performance of a subject that are caused by drowsiness are accompanied by spectral changes in electroencephalograms (EEGs). Furthermore, some studies have also shown EEG correlates of behavioral lapses (Makeig and Inlow 1993, Kecklund and Akerstedt 1993, Jung and Makeig 1995, Peiris *et al* 2006, Davidson *et al* 2007). These fundamental findings of EEG signatures of drowsiness and lapses, including power spectra (Lal *et al* 2003, Lin *et al* 2005, 2006, Peiris *et al* 2006, Davidson *et al* 2007, Yeo *et al* 2009, Johnson *et al* 2011, Khushaba *et al* 2011) and autoregressive features (Rosipal *et al* 2007, Zhao *et al* 2011), could then be used to develop various on-line/off-line neuroergonomic systems for monitoring drowsiness, fatigue, and behavioral lapse in task performance.

Much work has also been undertaken to assist individuals in combating drowsiness and/or to prevent lapses in concentration. Dingus *et al* (1997), Spence and Driver (1998) proposed the use of warning signals to maintain drivers' attention. The warning signals can be auditory (Spence and Driver 1998, Lin *et al* 2009), visual (Liu 2001), tactile (Ho *et al* 2005) or mixed (Liu 2001). These cited studies all revealed that arousing warning signals (feedback) considerably improve task performance. Furthermore, using arousing warning signals may effectively reduce the number of lapses of attention and thereby prevent devastating consequences. Our previous studies (Lin *et al* 2009) have demonstrated that an arousing tone-burst with a frequency of 1750 Hz can help subjects to maintain optimal driving performance. More recently, we demonstrated EEG dynamics and behavioral changes in response to arousing auditory signals that were presented to individuals who were experiencing momentary cognitive lapses in a sustained-attention task (Lin *et al* 2010). However, the study also showed that auditory feedback sometimes failed to arouse drowsy subjects and that the EEG activity of these non-responsive episodes showed no neural response to the feedback (Lin *et al* 2010, Jung *et al* 2010). A pilot study (Jung *et al* 2010) applied machine-learning algorithms to assess the efficacy of the arousing feedback on drowsy subjects and showed that the post-stimulus EEG spectra could be used to estimate the effectiveness of the arousing signals with a moderate accuracy of 61%.

This study extends the aforementioned works (Lin *et al* 2009, 2010, Jung *et al* 2010) to provide a detailed analysis on EEG spectra of effective and ineffective feedback and enhance the accuracy of the feedback efficacy assessment system. The objective of this study was to develop a system that can accurately detect an ineffective auditory feedback so that the system can trigger additional arousing signals, e.g. auditory warning signals or other stimulus modalities, to reduce the possibility of catastrophic accidents. Integrating the lapse prediction/monitoring methods proposed in previous studies (Kecklund and Akerstedt 1993, Jung and Makeig 1995, Davidson *et al* 2007, Peiris *et al* 2011) and a warning system with a feedback efficacy assessment mechanism, would finally form a closed-loop system to predict and rectify behavioral lapses while driving.

2. Methods

This study used the EEG and behavioral data reported in our previous study (Lin *et al* 2010), but focused on methods that can monitor the changes in the EEG following the arousing warning signal delivered to users experiencing momentary cognitive lapses to predict the efficacy of arousing feedback.

2.1. Subjects

Eleven healthy participants aged 20–28 years (ten males and one female) with normal hearing participated in virtual-reality (VR) based highway-driving experiments. All subjects were free of neurological and psychological disorders and none abused drugs or alcohol. No subject reported sleep deprivation on the day before the experiments, and none had worked night shifts during the preceding year or traveled through more than one time zone in the preceding two months. To accurately evaluate their driving performance, the subjects were required not to have imbibed alcoholic or caffeinated drinks or to have participated in strenuous exercise a day before the experiments were performed. The Institutional Review Board of the Taipei Veterans General Hospital approved the experimental protocol. All experiments were performed in the early afternoon (13:30 $\pm$ 1 h) after lunch when the circadian rhythm of sleepiness was at its peak (Ferrara and De Gennaro 2001). All subjects were informed about the experimental procedures and the driving task process. All provided informed consent before they participated. Before the experiments, they practiced driving in the simulator to get acquainted with it and with the experimental procedures. After the experiments, they were also asked to complete a questionnaire.

2.2. Experimental equipment

VR-based monotonous highway-driving experiments were performed in a driving simulator that mimicked realistic driving situations in a dark, sound-reduced room. The VR scenes simulated driving at a constant speed (100 km h^{-1}) on a four-lane divided highway with the car randomly drifting away from the center of the cruising lane to simulate driving on non-ideal road surfaces or with poor alignment. The road was straight and monotonous and no traffic or other stimuli appeared in the VR scene, simulating a driving situation that is likely to induce drowsiness. The scenes were updated at 60 frames per second.

This study recorded 30-channel EEG data referentially against a linked mastoid reference using the NuAmp system (Compumedics Ltd, VIC, Australia) with a sampling rate of 500 Hz and a 16-bit quantization level. The EEG electrodes were placed according to the modified international 10–20 system (Homan *et al* 1987). The impedance between the skin and all EEG electrodes was calibrated to be less than 10 kΩ.

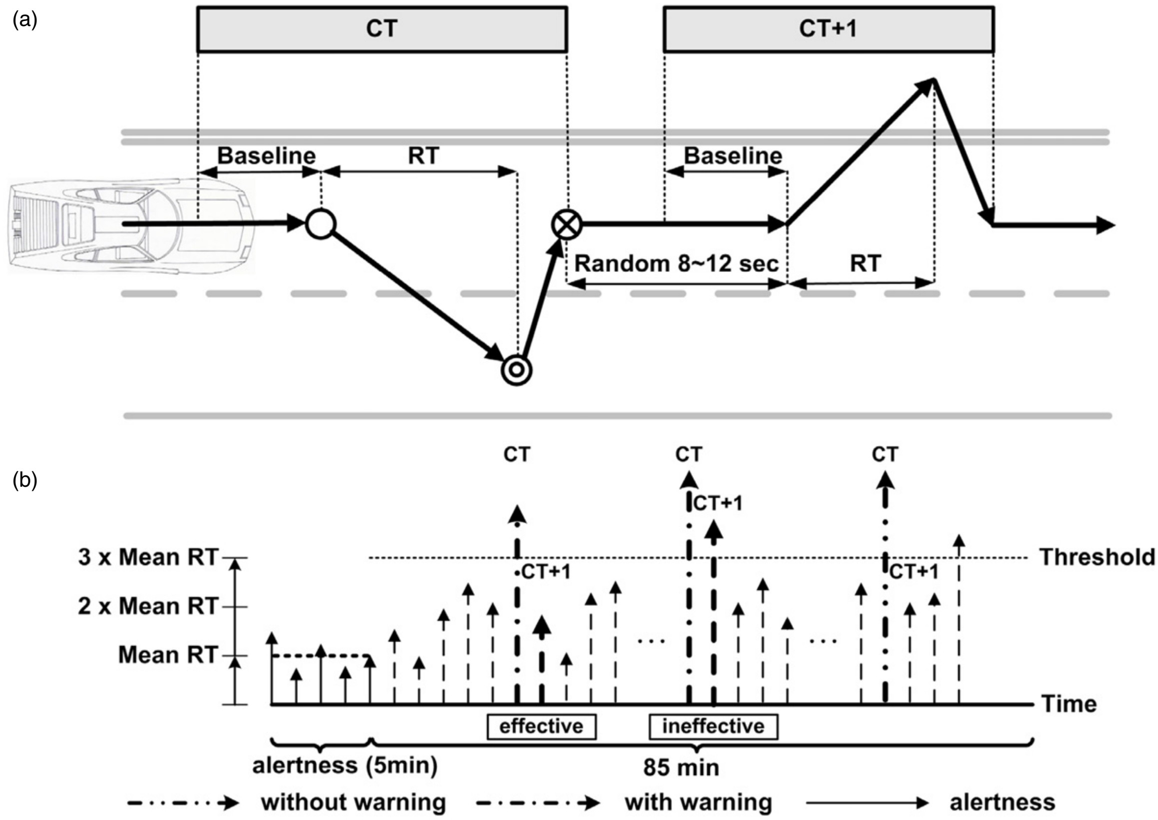

Figure 1. Experimental illustration. (a) Event-related lane-departure driving tasks. The solid arrows represent the driving trajectory. The empty circle represents the deviation onset. The double circle represents the response onset. The circle with the cross represents the response offset. The baseline is defined as the 3 s period prior to deviation onset. The RT of a driver is the interval from the deviation to the response onset. A trial starts at the deviation onset and ends at the response offset. The next deviation begins 8–12 s after the response offset. (b) The criteria for delivering auditory feedback during driving tasks. The height of an arrow represents the RT in a single trial. The warning feedback was delivered to the subject when the RT in the trial exceeded three times the mean RT of trials in the first 5 min of the task, when the subject was presumably alert and fully attentive to lane-departure events. Figure 1 is adapted from figure 1 of Lin *et al* (2010).

The EEG data were preprocessed, using a low-pass filter of 50 Hz and a high-pass filter of 0.5 Hz, to remove the line noise and the baseline drift, respectively, before being down-sampled to 250 Hz.

2.3. Experimental paradigm

This study implemented an event-related lane-departure driving paradigm (figure 1(a)) (Huang *et al* 2009) on the driving simulator to objectively and quantitatively measure both momentary event-related brain dynamics following lane-departure events and task performance fluctuations over long periods. Lane-departure events were randomly introduced every 8–12 s, causing drift at a constant speed towards the curb or into the opposite lane with equal probability. Subjects were instructed to steer the vehicle back to the center of the original cruising lane as quickly as possible. During the experiment, the vehicle trajectory and the time of the lane-departure event, the onset of response, and the end of response were recorded. The time interval between the deviation onset and the response onset was defined as the response time (RT) that presumably reflected the vigilance/arousal state of the subject (Huang *et al* 2008, 2009, Lin *et al* 2010).

Before the experiment, subjects were instructed to stay alert as much as possible and respond to the deviation event as soon as possible. During a 90 min experiment (figure 1(b)), subjects had to compensate for hundreds of lane-departure events and their performance tended to fluctuate over time. The first 5 min of each experiment was considered as the baseline period during which the subjects were presumably alert and fully attentive to the given task. Monitoring the experimental performance via a surveillance camera and the vehicle trajectory further ensured subject's alertness. All RTs in this period were averaged as the mean alert RT (0.50–0.85 s across subjects). During the remaining 85 min of the experiment, if the subject's RTs to lane-departure events exceeded three times the mean alert RT, the system would automatically deliver a 1750 Hz tone-burst to the subject in half of these trials (defined as the 'current trial' (CT)). Trials in which the warning signal was delivered to the subject were labeled 'with warning'. Those in which it was not were labeled 'without warning'. The auditory warning signal volume was set to a fixed level (∼68.5 dB), which was noticeable, but not too loud. The following trial (CT+1) is the trial following the CT in which the participant is drowsy. If the RT of CT+1 was shorter than double the mean alert RT, the warning signal delivered in the CT was defined as an 'effective warning'. On the other hand, if the RT of the CT+1 trial was longer than three times the mean alert RT, the warning feedback was defined as an 'ineffective warning'.

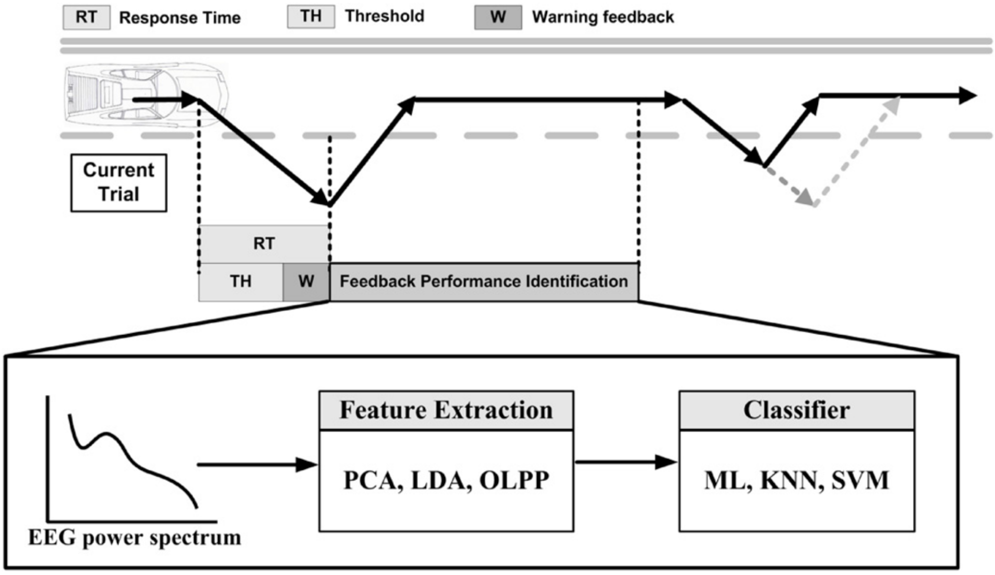

Figure 2. Procedure for assessing feedback performance. Threshold (TH) is three times the mean alert RT. If RT exceeds TH, warning feedback is delivered to the driver. The efficacy of a warning feedback action is assessed by a system that uses time–frequency transform, feature extraction and a machine-learning classifier.

2.4. EEG data analysis

The continuous EEG signals were segmented into 115 s trials, from 15 s preceding and to 100 s following the arousal stimuli. The EEG signals that were considerably contaminated by artifacts (muscle activity, blinks, eyes movement and environmental noise) were manually eliminated to minimize their influence on subsequent analysis. Independent component analysis (ICA) (Bell and Sejnowski 1995, Makeig *et al* 1997) implemented in EEGLAB (version 5.03b) (Delorme and Makeig 2004) was then used to separate the 30-channel EEG signals into 30 independent components (ICs), based on the assumption that the EEG signals at the sensors were linear mixtures of the activations of distinct brain sources whose time courses were statistically independent of each other.

To find comparable ICs across subjects, components obtained from various subjects were grouped into component clusters based on their scalp maps, equivalent dipole locations and baseline power spectra of component activations (Delorme and Makeig 2004). Time courses of component activations were then transferred to the frequency domain by fast Fourier transforms (FFT). The resultant time–frequency estimates consisted of 30 frequency bins from 2 to 30 Hz with a frequency resolution around 0.25 Hz.

2.5. EEG pattern recognition in system for assessing feedback efficacy

As shown in the previous study (Lin *et al* 2010), auditory feedback does not always arouse subjects in a simulated driving task. An analogy to this situation is that some people use more than one alarm clock to wake themselves, but the alarm is still sometimes ineffective even if they physically have to turn the alarm off. The most important issue is whether the brain is awake/alert or not. This study proposes a feedback efficacy assessment system that automatically evaluates the changes in subjects' EEG patterns following the delivery of arousing warning signals. Feedback-induced EEG spectral features were input to machine-learning classifiers to detect ineffective warning feedback, enabling an additional warning signal to be repeatedly delivered to the subjects until an effective EEG signature (the spectral suppression in the theta- and alpha-bands of the bilateral occipital component) was identified (Lin *et al* 2010, Jung *et al* 2010).

Across all 11 subjects, the total number of trials with warnings was 155, of which 30 trials were referred to as having an 'ineffective warning' and 125 trials were referred to as having an 'effective warning' according to the above-mentioned criteria. The log spectra of component activations following the onsets of arousing signals were extracted (see section 3.2) as features for assessing the efficacy of the arousing feedback. Figure 2 shows the signal-processing pipeline of the feedback efficacy assessment system. If the system detects that the warning is not effective, the warning signals are delivered to users repeatedly.

The IC activities in each trial were first transformed into time–frequency data (EEG power spectrum in figure 4) using FFTs with 4 s moving windows, advancing in intervals of 0.7 s, which approximately equaled the mean short-RTs (alert RTs) across all subjects. Then, the maximum (dB) power across 17 frequencies bins (4–12 Hz, 0.5 Hz resolution) was selected as the power at each time point. This procedure resulted in 20 estimates per trial of log EEG power immediately following the onsets of arousing signals. Several methods of feature extraction, including principal component analysis (PCA), linear discriminant analysis (LDA) and orthogonal locality-preserving projection (OLPP), were then used to extract the informative features from the 20-dimensional data, to estimate the efficacy of the arousing feedback. Finally, three widely-used classifiers—the support vector machine (SVM) (Chang and Lin 2001), the Gaussian maximum likelihood

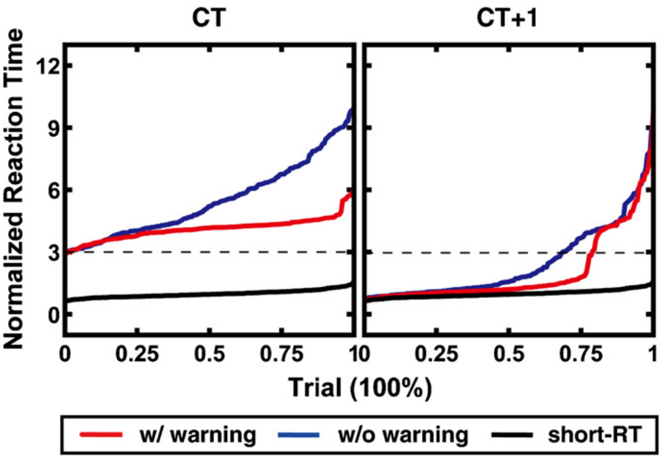

Figure 3. Comparison of RTs following lane-departure events with and without the delivery of auditory feedback. The black horizontal dashed line at the CT and CT+1 represents the feedback onset (three times the mean reaction time). The traces represent the cumulative percentage (y-axis) of the CTs and the CT+1 that are sorted by normalized RTs (y-axis). The blue, red, and black traces represent the sorted trials without a warning, with a warning, and short-RT (alert), respectively. Figure 3 is adapted from figure 2(a) of Lin *et al* (2010).

classifier (ML) (Hoffbeck and Landgrebe 1996) and the k-nearest neighbor classifier (KNN) (Bay 1999)—were trained with the input data and their classification performances were compared. Furthermore, to avoid the confounding issue of classifying unbalanced numbers of effective and ineffective trial samples and small sample size, a bootstrap cross-validation method (Fu *et al* 2005) was performed to bootstrap datasets with replacements from all trials, in which each bootstrap subset had equal numbers (30 for each bootstrap set of effective and ineffective trials) of samples in every class. For each bootstrapped dataset, five-fold cross-validation was utilized to estimate classification accuracies. This procedure was repeated 30 times.

2.6. Statistical analysis

The RT and EEG power were not normally distributed, so nonparametric statistical tests were performed to analyze the data. Bootstrapping (EEGLAB toolbox, University of California, San Diego) was used to test the statistical significance of changes in the EEG power in selected frequency bins from 2 to 30 Hz (with a frequency resolution of 2.5 Hz). The EEG spectra were also normalized by dividing the spectral power by the standard deviation of the spectral distribution. To obtain group statistics, the intrinsic inter-subject RT differences were normalized by dividing RTs by the mean RT. The Wilcoxon rank sum test (Matlab statistical toolbox, Mathworks) was performed to identify significant differences among combinations of feature extractions and classifiers for assessing the efficacy of the feedback. The accuracies are presented as mean ± standard deviation (SD).

3. Results

3.1. Effects of arousing warning signals

Figure 3 shows the comparison of the RTs between trials with and without the arousing feedback. In both CT (left panel), and CT+1 (right panel), the RTs in the trials with the warning signal (red traces) were significantly shorter than those in the trials without warning signals (blue traces). However, as shown, in some (∼20%) of the CT+1 trials with the warning signal (red trace) RTs still exceeded three times the normalized RT. This result reveals that the arousing feedback was not effective in all of the trials, and the RT of those trials in which the signals were ineffective was as long as that in the trials without feedback, even longer.

3.2. Effects of feedback on brain activities

The left panel of figure 4 compares the baseline power spectra of bilateral occipital components of the long-RT CTs (red, light blue, and blue traces) with that of the short-RT CTs (black traces), where the power spectra are calculated from the component activities recorded prior to the deviation onset. Consistently with previous findings (Makeig and Inlow 1993, Campagne *et al* 2004, Makeig and Jung 1996, Jung *et al* 1997, Lal and Craig 2002, Horne and Baulk 2004, Pastor *et al* 2006, Huang *et al* 2008, 2009, Jap *et al* 2011), the power spectra exhibited tonic increases in the theta (4–7 Hz), alpha (8–12 Hz), and beta (13–30 Hz) bands in long-RT trials. The right panel of figure 4 compares the baseline spectra of the component activities in the trials immediately following an ineffective warning (light blue trace), effective warning trials (red trace) and no warning (blue trace). The spectra of the trials with effective warning were significantly lower than those of the trials without warning and with ineffective warning (bootstrap significance test, size = 5000, EEGLAB toolbox, UCSD, $p < 0.01$), suggesting that the auditory warning signals could induce a spectral decrease in the power baselines. The statistically significant spectral differences were most prominent in the theta and alpha bands. Note that the spectra of the ineffective trials (light blue trace) were similar to those trials without a warning (blue trace).

Figure 5 shows time courses of the feedback-induced alpha- (upper panel) and theta-band (lower panel) spectral changes in the bilateral occipital area for trials following ineffective warning (light blue trace), effective warning trials (red trace) and no warning (blue trace), compared to those of the short-RT trials. Before the feedback/response, the theta- and alpha-power baselines of the long-RT trials (blue, red and light blue traces) were considerably higher than those of the short-RT (alert) trials. After the feedback/response onset, the alpha- and theta-power abruptly decreased by over 5 and 10 dB, respectively. Following the responses of the subjects, the spectra of ineffective (blue trace) and non-feedback (dark blue) trials rapidly rose from the alert baseline to the drowsy level in 5–10 s. The EEG power of effective trials, however, remained low for ∼40 s. The green horizontal lines mark the time points when the difference between the spectra of trials with effective warning and those of trials without warning

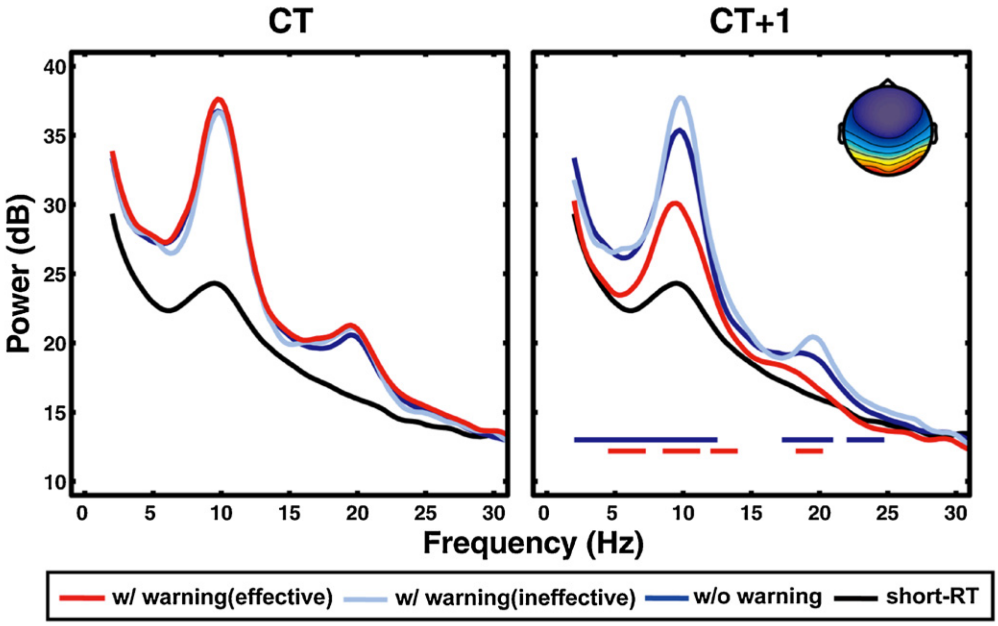

Figure 4. Component spectra of trials with an effective warning, with an ineffective warning and without a warning and those of the short-RT (alert) trials. The spectra were calculated from the time series of the bilateral occipital components separated by ICA. The black traces represent the spectra of the alert trials. A CT is a trial with an RT that exceeds three times the mean RT. Warning feedback is delivered only in a CT. The red, light blue and blue traces are the component spectra of trials with an effective warning, with an ineffective warning and without a warning, respectively. For CT+1, the blue horizontal line marks the frequencies at which the spectral differences between the trials without a warning and with an effective warning were statistically significant (bootstrap significance test, size = 5000, EEGLAB toolbox, UCSD, $p < 0.01$). The red horizontal line marks the frequencies at which the spectral differences between the trials with an ineffective warning and with an effective warning were statistically significant (bootstrap significance test, size = 5000, EEGLAB toolbox, UCSD, $p < 0.01$). (Notably, the spectra in this figure were calculated from the EEG data that were recorded 3 s before the onset of land deviation.)

Table 1. The accuracies of estimating efficacy of feedback using different feature extraction methods and classifiers[a].

	Feature extraction			
Classifier	None	PCA	LDA	OLPP
ML	61.5 ± 6.4	77.8 ± 5.4	77.4 ± 5.2	69.6 ± 5.7
KNN	71.9 ± 6.1	74.6 ± 5.3	73.8 ± 4.9	75.8 ± 5.4
SVM	73.7 ± 5.4	76.1 ± 5.4	76.5 ± 4.5	71.7 ± 5.5

[a] All accuracies are shown as (mean ± standard deviation) for all trials.

was statistically significant (bootstrap significance test, size = 5000, EEGLAB toolbox, UCSD, $p < 0.01$). The spectral difference between the trials without and with an effective warning was statistically significant from 5 to 16 s in the alpha band and from 5 to 18 s in the theta band (bootstrap significance test, size = 5000, EEGLAB toolbox, UCSD, $p < 0.01$). Furthermore, the spectral difference between the trials with effective and ineffective warnings was statistically significant from 5 to 14 s in both the alpha and theta bands.

3.3. Performance of the feedback efficacy assessment system

Table 1 and figure 6 show the results of classifying the trials with effective and ineffective warnings. To avoid bias in classifying unbalanced numbers of trial samples (125 effective versus 30 ineffective), each training and testing dataset comprised equal numbers of randomly selected effective and ineffective trials. In table 1, most of the classification accuracies exceeded 70%, and some even exceeded 75%. Feature extraction affected the performance of the ML classifier significantly (no feature extraction: 61.5% versus with feature extraction: 77.8%, 77.4% and 69.6%) (Wilcoxon rank sum test, DF = 28, $p < 0.05$). Using KNN yielded accuracies that all exceeded 70%. However, the performance of KNN achieved by using the data without feature extraction was significantly lower than that with feature extraction. Overall, using PCA with an ML classifier achieved the best performance (mean: 77.8% ± 5.4). Using the SVM as the classifier generally yielded a robust performance, regardless of whether feature extraction was used.

Table 2. Confusion matrix of estimating efficacy of feedback[a].

		Trial type		
Classifier	Trials classified	Effective	Ineffective	Overall accuracy[b] (%)
ML	Effective	682	218	77.8%
	Ineffective	182	718	
KNN	Effective	664	236	74.6%
	Ineffective	222	678	
SVM	Effective	640	260	76.1%
	Ineffective	170	730	

[a] The performance of classifiers through PCA feature extraction.
[b] The testing was repeated 30 times.

Table 2 shows the confusion matrices obtained by using PCA with ML, KNN, and SVM, where the total number of the testing sample was 900. The sensitivity of the ML classifier (for effective-feedback trials) was 75.8% (correctly

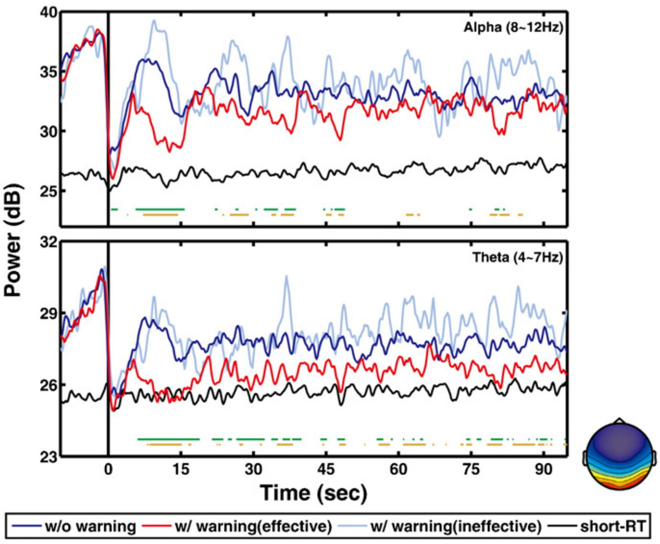

Figure 5. Averaged (across subjects, sessions and trials) spectra of bilateral occipital components following long-RT trials in the (upper) alpha and (lower) theta bands. All trials were aligned with the response onset (vertical black solid line). The blue, red, light blue, and black traces are the averaged spectral time courses of trials without a warning, with an effective warning (RT $< 2 \times$ alert RT) and with an ineffective warning (RT $> 3 \times$ alert RT) as well as alert trials, respectively. The green horizontal lines mark the time points when the differences between the spectra in trials with an effective warning and without a warning were statistically significant (bootstrap significance test, size = 5000, EEGLAB toolbox, UCSD, $p < 0.01$). The brown horizontal lines mark the time points when the spectral differences between trials with an effective warning and those with an ineffective warning were statistically significant (bootstrap significance test, size = 5000, EEGLAB toolbox, UCSD, $p < 0.01$).

recognized samples: 682), and its specificity (for ineffective-feedback trials) was 79.8% (correctly recognized samples: 718). The sensitivity of the KNN classifier (for effective-feedback trials) was 73.8% (correctly recognized samples: 664), and its specificity (for ineffective-feedback trials) was 75.3% (correctly recognized samples: 678). The sensitivity of the SVM classifier (for effective-feedback trials) was 71.1% (correctly recognized samples: 640), and the specificity (for ineffective-feedback trials) was 81.1% (correctly recognized samples: 730).

4. Discussion

Many studies (Makeig and Inlow 1993, Campagne *et al* 2004, Makeig and Jung 1996, Jung *et al* 1997, Lal and Craig 2002, Horne and Baulk 2004, Pastor *et al* 2006, Huang *et al* 2008, 2009, Jap *et al* 2011) have shown EEG correlates of drowsiness (or fatigue) and explored the feasibility of EEG-based drowsiness detection and monitoring in sustained-attention tasks. Specifically, theta power increases as task performance declines (Makeig *et al* 1993, 1995, 1997, Lal and Craig 2002). Furthermore, Peiris *et al* (2006), Davidson *et al* (2007) have reported that EEG power increases during lapses in delta, theta, and alpha bands, although correlations were moderate. These findings led to foundational insights into neural correlates of drowsiness and behavioral lapses.

Our previous studies (Lin *et al* 2009, 2010, Jung *et al* 2010) have also explored the use of tone-bursts to arouse drowsy subjects in a simulated driving task, Lin *et al* (2010) showed that, across subjects and sessions, behavioral performance during drowsiness was accompanied by characteristic spectral augmentation in the alpha- and theta-band spectra of a bilateral occipital component. The findings confirmed the relationship between theta and alpha power and task performance in simulated driving tasks reported in Lin *et al* (2010). This study extended our previous work (Lin *et al* 2009, 2010, Jung *et al* 2010) by providing a very detailed examination of brain dynamics and behavioral performance following effective arousing feedback, compared to that following ineffective feedback. Furthermore, this study explored the feasibility of using EEG spectra and machine-learning algorithms to assess the efficacy of arousing feedback.

The results of this study provide direct evidence that the EEG spectra following effective feedback differ significantly from those following ineffective feedback. The behavioral results in this study indicate that auditory feedback stimulated prompt compensatory responses, arousing the subjects such that the RT in the following lane-departure trials were significantly shorter than those of long-RT trials that were not followed by auditory feedback, demonstrating the advantage of using arousing feedback in a sustained-attention task (figure 3).

The RTs of trials following feedback were still longer that those of short-RT trials, suggesting that the subjects were not aroused to full alertness. This result may follow partially from the difficulty of adapting the auditory neurons to pure tones or pure tone-bursts (Ulanovsky *et al* 2004). Additionally, this study showed that the RTs of some trials following feedback were still more than three times longer than the mean alert RT (threshold), revealing that the auditory feedback was not always effective.

The baseline power of the bilateral occipital component was significantly lower in short-RT trials than in long-RT (or drowsiness) trials (figure 4, left panel) in the lane-keeping driving task. The bilateral occipital component also exhibited a considerable decrease in baseline power in the theta and alpha bands following effective auditory feedback (figure 4, right panel). The direction of spectral changes following auditory feedback was expected to be toward the baseline power of the short-RT trials (trials of alertness), suggesting that auditory feedback assisted subjects in reducing their drowsiness, as reflected in both behavioral performance and brain activities. Furthermore, the (pre-stimulus) baseline theta- and alpha-band power of the CT+1 trials that were followed by effective feedback were significantly lower than those of the trials that were followed by ineffective feedback (figure 4).

The spectral difference between the effective and ineffective trials was statistically significant at 5–14 s in the alpha and theta bands (figure 5, brown horizontal line) following response onset. Furthermore, the spectra of trials following auditory feedback and of trials without feedback differed significantly at 4–16 s in the alpha band and at 4–40 s in the theta band (figure 5, green horizontal line). The lack of a significant spectral difference at 0–5 s and at 16–23 s in the theta band might be attributed to phasic spectral

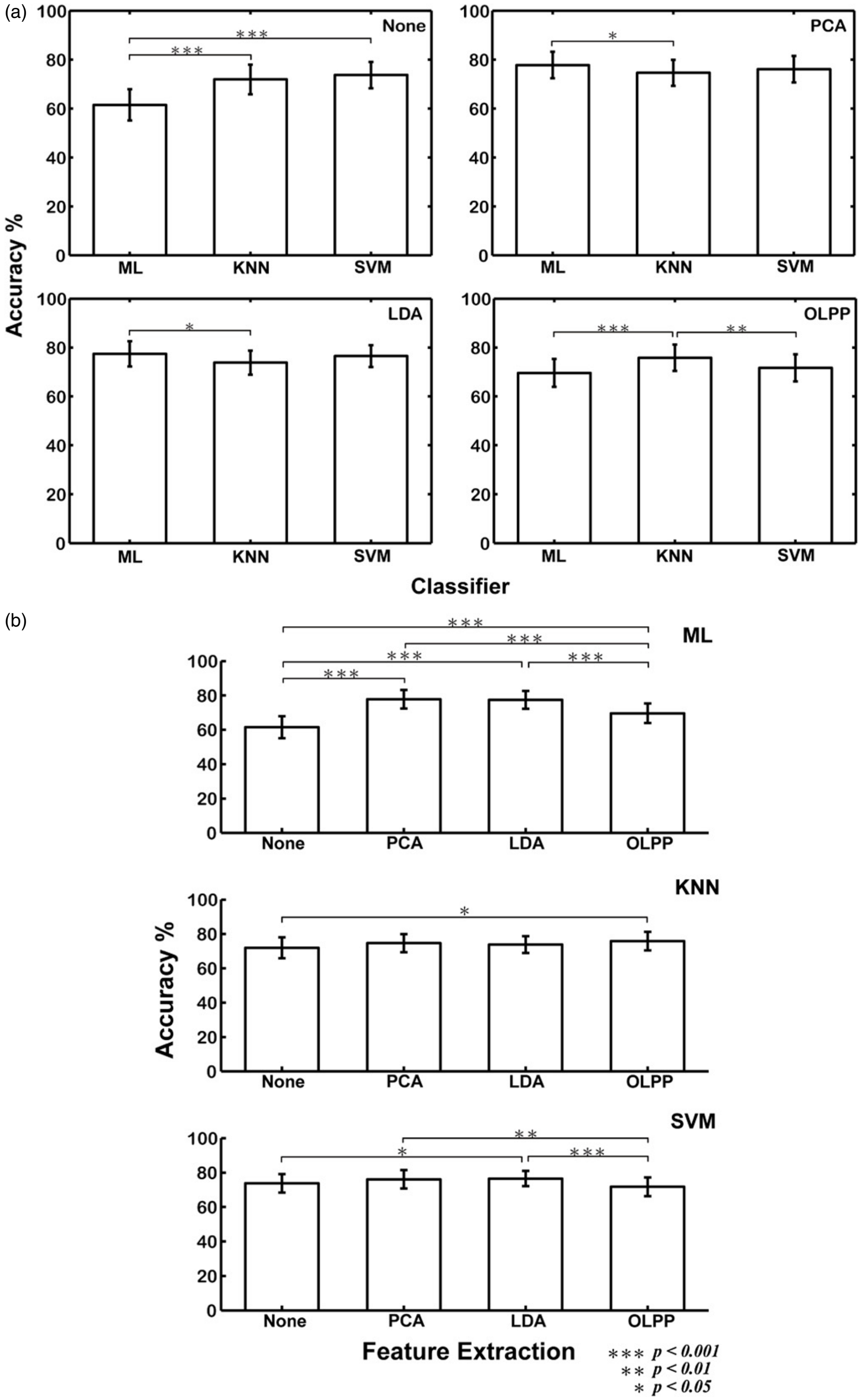

Figure 6. Comparison of accuracies of estimates of efficacies of feedback for various combinations of feature extraction and classifiers (Wilcoxon rank sum test, DF = 28, $p < 0.05$). (a) Comparison of performance of classifiers using different feature extractions. (b) Comparison of performance of feature extractions using different classifiers.

suppression that is induced by lane-deviation and a subject's response onsets. The effects of effective auditory feedback on the theta-band power suppression could last for at least 35 s.

In summary, spectral changes of the bilateral occipital component cluster accompanied the behavioral results that are shown in figure 3. The baseline power of trials following auditory feedback did not completely return to that of the trials of alertness. Furthermore, auditory feedback might be ineffective.

This study then demonstrated the feasibility of assessing the efficacy of arousing feedback by monitoring spontaneous EEG spectra with machine-learning algorithms. One might argue, why not require subjects' behavioral responses to ensure the efficacy of the arousing feedback? As in the operation of any alarm clock, subjects must physically stop the alarm from buzzing. In our driving experiments, the auditory feedback always agitated prompt compensatory responses from the subjects. However, the subjects still failed to respond to the next lane-deviation event in a timely fashion (which is the condition that defines an ineffective trial). Thus, a more reliable approach is to assess the efficacy of the feedback and the level of alertness by directly measuring their brain activities. Tables 1 and 2 present the performance of the proposed feedback efficacy assessment system. Different combinations of feature extraction methods and classifiers would affect the performance and applicability of the system. When no feature extraction is used in assessing feedback efficacy, the accuracy of classification by ML was worse than that by KNN and SVM. Feature extraction methods (particularly PCA and LDA) considerably improved the performance of ML. OLPP improved the performance of KNN. The accuracies that were achieved using SVM and KNN classifiers were all over 70% in any feature extraction, even without feature extraction. For the SVM classifier, PCA and LDA outperformed both OLPP and the method without feature extraction.

Previous studies have demonstrated the feasibility of using EEG to predict the possibility of lapses (Kecklund and Akerstedt 1993, Jung and Makeig 1995, Davidson *et al* 2007, Peiris *et al* 2011). Combining the proposed methods and the results of this study, a closed-loop lapse prediction and management system might be constructed to continuously assess the cognitive states of drivers by observing their EEG changes. The system can deliver arousing warning signal to a driver experiencing momentary cognitive lapses. Then, feedback-induced EEG spectral features can be extracted and fed into machine-learning classifiers to detect ineffective warning feedback, and an additional warning, if needed, can be delivered to the driver again.

However, a limitation at the present stage is the 14 s window length of EEG used for accessing the efficacy of arousing feedback, because the spectral difference between the effective and ineffective trials were most prominent during 5–14 s in the alpha and theta band after the onsets of arousal feedback. We are currently exploring an alternative stimulus and EEG markers that can reduce the estimating time.

5. Conclusion

This study demonstrates that auditory feedback aroused subjects such that the RTs in the following lane-departure trials CT+1 were significantly shorter than those in trials without auditory feedback. This study also shows that the EEG spectra of trials following effective feedback differed significantly from those of trials following ineffective feedback. This study further proposes and demonstrates the feasibility of a feedback efficacy assessment system that can estimate the efficacy of arousing feedback by monitoring the changes in EEG spectra following such feedback.

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