Detecting an operator's attention state in a continuous passive control task using a portable electro-encephalographic brain-computer interface

Yuriy Mishchenko[1] and Murat Kaya[2]

[1]Izmir University of Economics, Izmir, Turkey
[2]Toros University, Mersin, Turkey

Abstract

Advances in robotics and industrial and machinery automation had resulted in novel operating environments in which the reduction of operator's workload makes it difficult for the operators to maintain focus on corresponding control tasks. The problem of ensuring continuous operator's attention during passive or low-intensity control tasks, thus, is identified as an important problem facing modern applications. We develop a system for detecting operator attention states in a general passive control task based on a portable electroencephalographic Brain-Computer Interface. Our system uses a wireless EEG acquisition component based on modified EPOC EEG device and a special SVM state classifier working with the time-frequency representation of the EEG data. Our system automatically identifies operator's attention states based on the patterns of his or her electroencephalographic brain activity. We test the developed system using a simulated low-intensity control task. We demonstrate the ability of that system to detect focused, unfocused and sleepy states of operators with close to 90% accuracy. We find that the EEG patterns associated with different attention states vary significantly among individuals, and thus our system is trained individually for each operator. We find that the highest contribution to the attention state detection comes from the frontal and parietal EEG electrodes and 1-5 Hz and 10-15 Hz EEG frequency bands.

Keywords : attention state classification; drowsiness detection; passive control task; continuous control task; electroencephalography; brain-computer interface; support vector machine classification

1. Introduction

One of major problems faced in modern engineering and applications is ensuring the attentiveness of the operators of increasingly automated and autonomous processes during associated operator control tasks. Rapid developments in automation and robotics have led to dramatic changes in the way modern operators have to interact with controlled systems. In many applications, the control tasks of a complex machinery or a process requires only passive engagement from the operator during the system's normal operations. The resulting low cognitive demand on the operator easily leads to him or her losing focus or experiencing sleepiness. Such cognitive conditions can result in the loss of ability to react to emergency situations, potentially leading to development of dangerous situations. The problem of real-time detection of attention states is therefore of high interest to applications [1-20].

Brain Computer Interface (BCI) is a direct communication channel between a human and an external device. Brain–computer interfaces present novel communication and control pathways that do not depend on the brain's normal output channels such as peripheral nerves and muscles. The classical definition of BCI states "A brain–computer interface is a communication system that does not depend on the brain's normal output pathways of peripheral nerves and muscles" [29].

In this work, we pursue the development of a system for detecting an operator's attention states in the context of a general low-intensity control task using an electroencephalographic Brain-Computer Interface (EEG-BCI). The problem that we consider in this work is of substantial practical interest for many applications, where the human operators need to remain largely dormant as passive supervisors of largely automated machinery or processes, while still retaining a sufficient amount of concentration and responsiveness. The applications thus covered include the supervision of robotized assembly lines, automated industrial processes, security rooms, driver-assisted or fully robotic vehicles, drone aircrafts, as well as a variety of similar tasks.

In the past, the problem of detecting attention loss or drowsiness had been investigated in the context of automotive applications. In the context of detecting car drivers' drowsiness or attention fatigue, different systems had been investigated in the literature, which can be divided into three main categories: The systems for tracking vehicle parameters such as steering wheel movements, position in lain, accelerator pedal [16,19]; detecting certain drivers' visual behaviors such as yawning, eyes closing, head position [2,11,16,19]; and monitoring drivers' physiological parameters such as electrocardiogram (ECG), electrooculogram (EOG), and electroencephalograms (EEG) [2,11,16,19]. For example, the heart rate is known to vary significantly during different stages of drowsiness, is almost impossible to fake, and can be easily detected via the ECG signal. Similarly, EOG signal had been used in the literature to measure the drivers' eye movement, eyelid opening and closing, etc., allowing the estimation of driver's sleepiness in the manner similar to that of the video-monitoring systems.

Unfortunately, such systems do not allow straightforward generalization to different tasks, such as the passive control task of interest in this paper. For instance, the design of the systems based on monitoring the vehicle parameters is typically very specific to the auto driver's activity and it is not clear at all how such a system can be modified to work with, for instance, the operators of a robotized assembly line. While even drowsy drivers in a car driving task engage typically in various driving and micro-corrective behaviours, in a passive control task the operator even the normal conditions is typically motionless, introducing a substantial difference in the attention loss or drowsiness detection task. Similar problems exist with the visual cue monitoring-based systems. As such, the attention loss and drowsiness detection systems based on monitoring physiological cues, such as EEG, are of main interest in this paper.

EEG is unique among the above approaches in that it allows monitoring directly the drivers' cognitive states by measuring the brain activity. Drowsiness and other cognitive states can be expected to give rise to certain patterns in the EEG signal. In Ref. [21], the authors study the EEG recordings made in the context of detecting the onset of sleepiness in car drivers and find that the EEG activity can predict the drivers' sleepiness. In Ref. [22], it is shown that the alpha-wave EEG activity increased in the freight train drivers during night time, indicative of their sleepiness. In Ref. [23], a detection of sleepiness onset in car drivers is studied based on theta and alpha-waves in the EEG signal. In Ref. [24], the detection of EEG alpha-waves is used to propose a system for estimating drivers' fatigue and sleepiness while in real traffic. A similar study isfound in Ref. [25], where the authors report the association of alerted and drowsy states in car drivers with the changes in beta and alpha-wave EEG activities.

The system for detecting loss of attention or drowsiness in this work makes use of a portable EEG-acquisition device based on a modified Emotiv EPOC EEG headset and a SVM-based signal processing algorithm in time-frequency domain for detecting three "focused", "unfocused" and "sleepy" cognitive states of human operators in passive control tasks. We test that system using the example of a virtual low-intensity supervisory task and show that it can detect the said three cognitive states with high accuracy.

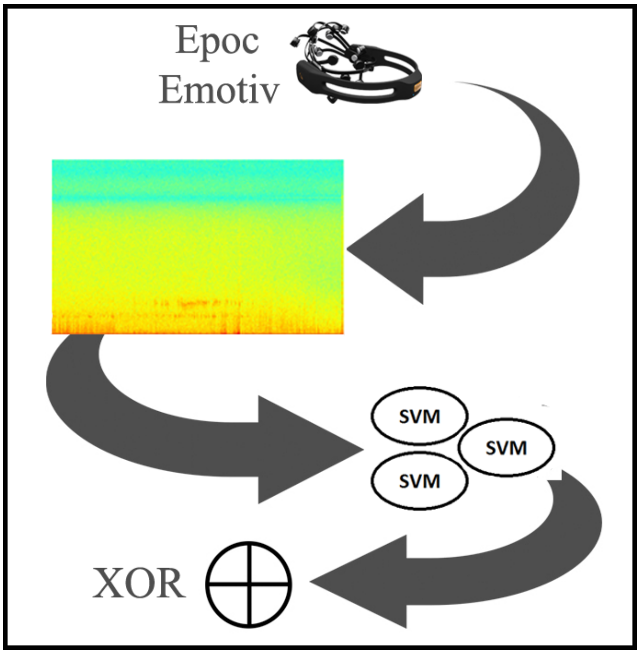

Figure 1. A schematic representation of the system for monitoring the attention state of an operator described in this work. The EEG data is first collected using a modified EPOC EEG-headset. The data is then transmitted to a computer over wireless Bluetooth connection and transformed into time-frequency domain using a short-time Fast Fourier transform. The power spectra of the signals from every EEG electrode are calculated at 1.0 second intervals over 15 seconds Blackman window and passed as the input to a set of three SVM classifiers, separately trained to detect one attention state of an operator. The output of the SVM classifiers is combined via 3-way exclusive-OR to produce the estimate of the operator's attention state at current time point.

2. Materials and Methods

In this section we describe the details of our realization of an electroencephalographic brain-computer interface (EEG-BCI) -based system for monitoring the attention states of operators of general purpose processes in a low-intensity or predominantly passive control task.

The EEG data in our system was acquired using a modified EPOC EEG device (EMOTIV, San

Francisco). The EPOC device is a portable EEG headset providing 12 channel EEG-data at 128 Hz sampling rate and resolution of approximately 0.5 microvolt. The device is using a system of saline electrodes assembled onto a fixed plastic spider-cap that allows fast application and use by a single person. The headset connects to a computer via wireless Bluetooth connection, over which it transmits the EEG data. An API is available in the form of a DLL library, called EMO-ENGINE, which allows the device's raw EEG data to be accessed and monitored manually via the calls to that DLL library.

We modified the headset by physically removing the plastic spider-cap and replacing the electrodes onto a custom-made EEG-cap with the new positions being F3/F4, Fz, C3/C4, Cz, Pz, T3/T4, T5/T6, according to the international 10/20 system, instead of the original AF3/AF4, F3/F4, F7/F8, FC5/FC6, T7/T8, P7/P8 and O1/O2. This was done in order to achieve more uniform coverage of the scalp by the electrodes, such as in the 10/20 system, whereas the original electrode arrangement in the EPOC device is heavily skewed towards frontal lobes. Out of the above electrodes, four electrodes T3/T4 and T5/T6 were determined to serve as the reference electrodes in EPOC device and, thus, did not provide useful EEG data. Thus, our modified EEG acquisition system provided a total of 7 real-time EEG data-channels.

We acquired the raw EEG data using a custom interface program written for EPOC device in Matlab, relying on the EMO-ENGINE DLL library. Acquired EEG data was transformed into the time-frequency domain by calculating spectrograms using the short-time Fourier transform with Blackman window of specific length. The short-time Fourier transform is defined by

$$X(t,\omega) = \sum_{t'=-\infty}^{\infty} x(t')w(t'-t)e^{-j\omega t'},$$

where $x(t)$ is the signal sequence and $w[t]$ is the Blackman window function [27, 28]. We experimented with the size of the Blackman window $w(t)$ in the short-time Fourier transform, including the sizes of 1, 5, 15, 30 and 60 seconds. Larger window size provided for a greater degree of smoothing of the obtained spectral maps, however, smaller window size offered higher temporal sensitivity of such maps. In order to achieve the compromise of lesser noise but higher temporal responsiveness of our system, and intermediate length of the Blackman window had to be chosen. We found empirically that the window of size of 15 seconds appeared to be suitable both from the point of view of suppressing noise and offering reasonable temporal responsiveness of our system. Spectrograms represent the power spectral density (PSD) of the calculated short-time Fourier transforms as the function of frequency and time, defined as $S(t,\omega) = |X(t,\omega)|^2$.

Thus, for the processing of the acquired EEG signal, the spectrograms $S(t,\omega)$ were calculated from the raw EEG data for each EEG channel using the 1024-point short-time Fourier transform with the Blackman windows of size 15 seconds and the time-step of 1 second. This resulted in the spectrograms spanning the frequencies from 0 to 64 Hz at the frequency-step of 0.125 Hz, calculated every 1 second. These spectrograms were subsequently restricted to the frequencies strictly greater than zero and smaller than 18 Hz (that is, covering the standard EEG frequency bands Delta, Theta, Alpha and Beta), and then down-sampled into 0.5 Hz frequency-bins by calculating the average of the spectral power densities within each non-overlapping 0.5 Hz frequency band. Lastly, obtained spectrograms were smoothed in time by using 15 seconds running average. Thus obtained time-frequency domain EEG power densities were combined into a single feature-vector to be used for the classification of operators' attention states. For 7 EEG data-channels this produced a feature vector of 252 EEG spectral power values calculated at 1 second intervals.

We did not control for the artefacts in the EEG data. We observed that the classification algorithm below was able to learn to separate such artefacts by itself. Consequently, we did not observe any significant degradation in the performance in our data that could be attributed to the artefacts in the EEG data.

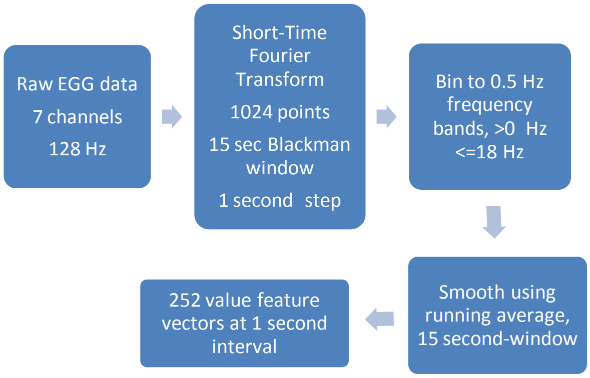

Figure 2. The sequence of the data processing steps for the raw EEG data used in this work.

To detect the operator's attention states from the EEG data, we designed a classifier consisting of three SVM classifier machines. SVM classifier is a two-class optimal linear classifier found from the principle of maximizing the class separation margin. That is, for a two-class set of examples (here – the feature vectors comprising the down-sampled and smoothed short-time Fourier transform of all EEG channels' data, s_t, above) the classification labels y_t are assigned via

$$y_t = sign(w^T s_t - b),$$

where the vector w and the scalar b are the parameters of the classifier selected by solving the soft margin maximization problem,

$$\arg\min_{\mathrm{w,b}} \left(\frac{1}{2}|w|^2 + C\sum \xi_t\right)$$

$$\text{s.t. } y_t(w^T x_t - b) \geq 1 - \xi_t, \xi_t \geq 0.$$

The labels $y_t \in \{-1,1\}$ here are the observations of the "focused", "unfocused", and "drowsy" attention states at each given point of time *t*, that is, corresponding to the operator being in focused or attentive, unfocused or inattentive (but not drowsy), or drowsy or sleepy state at a given time point. Each SVM classifier was trained to produce the output of "1" for one of the abovementioned states and "-1" for the others states. That is, the first SVM classifier was trained to respond only when the operator was observed to be in the "focused" state, the second SVM classifier was trained to respond only to the operator being in the "unfocused" state, and the third SVM classifier was trained to respond only to the "drowsy" state.

The final determination of the operator's attention state was performed based on the labels produced by these three classifiers from the 3-way XOR operation. More specifically, if one SVM classifier produced "1" and the other two produced "-1" for a given time's feature-vector s_t, then that time-bin was assigned the state-label of the responded classifier. If two or more classifiers produced "1" or all of them produced "-1", then the feature vector was labelled as "unclassified" and counted as an error against our system's performance.

The described system for operator attention state detection was trained and tested for each subject individually as well as for all subjects jointly.

In the case of individual training, the said three classifiers were trained using randomly selected 80% of all the data available for one participant and validated on 20% remaining data. This resulted in approximately 6000 different time points used in training and 1500 time points used in validation. The three SVM classifiers were trained using the Least Square method using the *svmtrain* function in Matlab [26]. The classifiers were operating on 252-element feature vectors, as described above. The "focused", "unfocused" and "drowsy" states were approximately equally represented in the training as well as the validation data.

In the case of joint training, the system was trained on a random 20% subset of the data comprising all EEG data collected for all participants. All the classifiers were trained in the same manner as above but using that mixed dataset. The performance of thus trained "generic" system was evaluated by cross-validation on that mixed dataset as well as individually for each participant.

3. Results

In order to test the system for detecting operator attention state, described in this work, we performed a series of experiments with live participants in virtual environment. The experiments were intended to model the participants' engagement in a low-intensity continuous-attention control task, which comprises the focus of this work.

More specifically, in the above experiments five volunteer participants engaged in the task of driving a passenger train using a computer simulator program "Microsoft Train Simulator". All participants were healthy individuals and were informed about the experiment's objectives and procedures, and signed informed consent form in accordance with the ethical guidelines of Toros University (Mersin, Turkey). In the course of a single experiment, the participants drove a modern locomotive "Acela Express" for 35 to 55 minutes on a part of a track from the "Amtrak-Philadelphia" route in the "Microsoft Train Simulator". The track comprised a part of the "Amtrak-

Philadelphia" route that was especially flat and featureless, so that the participants needed to provide little control-input except for the initial and the final segments of the track. The control-inputs comprised adjusting throttle and applying brakes. The participants were instructed to drive the train slowly at the speed of 40 mph, to increase the tediousness of the task.

The experiments were conducted during the evening hours between 7 pm and 9 pm, after the participants had their evening meal, increasing the tediousness factor. Each participant performed 7 experiments, at most one experiment in one day, with the two initial experiments used for participants' habituation and the last 5 experiments used to collect data. A total of 35 experiments had been performed.

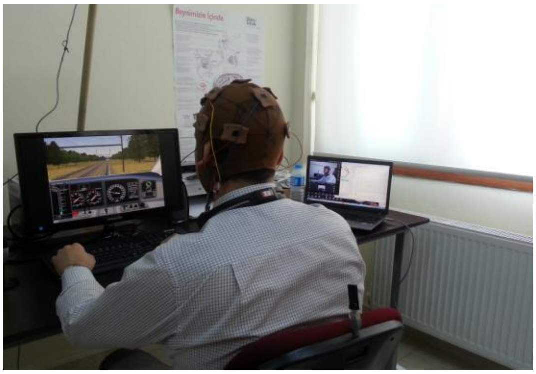

Figure 3. The organization of the virtual passive continuous control task used for testing the described EEG-BCI attention state detection system. In the experiments, participants engaged in controlling a simulated passenger train on a primarily featureless segment of track for the duration of 35 to 55 minutes.

During the experiments, the participants were instructed to attentively drive the train for the first 10 minutes of the track. After that, they were allowed to un-focus and stop paying attention to the train or the route, but were asked not to drowse or close their eyes for the next 10 minutes of the track. After that, the participants were instructed to relax freely at will for the remainder of the track, either with eyes open or closed as desired.

The state of the participants had been evaluated visually by an observer in the experiment, to evaluate whether the participants paid attention to the track, unfocused or dosed off with eyes closed as instructed prior to the experiment. Additionally, video record of the subjects in each experiment had been taken, and ambiguous moments were later examined from the video recordings. Additionally, a software reaction-time test had been performed every 3 to 5 minutes, by playing a low-volume low-frequency audio signal to the participants and requiring them to push a defined button on the computer keyboard. Using this information, the map of the subjects' cognitive states with time-resolution of 2 minutes had been constructed for each experiment.

The EEG data collected during the experiments was first pre-processed by converting to time-frequency domain, as described in Section 2. Obtained spectrograms were inspected visually. This revealed that different attention states of the participants, namely focused, unfocused and drowsy, could be visually associated in the EEG power spectra with certain features, Fig. 4. The “focused” and the “unfocused” states were associated with the enhancement or suppression of the EEG activity in the 1-10 Hz frequency band, with the most pronounced differences observed at the electrodes placed over the frontal lobe at positions F3, F4 and Fz. The drowsy state was observed to appear in the EEG spectrograms as continuous or intermittent bands of alpha-frequency EEG signal at 10 to 15 Hz, observed most prominently at the parietal lobe locations C3, C4, Cz and Pz.

The above preliminary examination of the EEG spectrograms suggested that the focused state of the participants could be characterized by the elevated levels of EEG activity in the frequencies of 1-10 Hz. This pattern was found to be distributed over the entire 1-10 Hz frequency range and not any narrow frequency band. The unfocused state of the participants could be characterized by reduced levels of the EEG activity at all frequencies. The drowsy state could be characterized by elevated activity in alpha band, at the frequency 10-15 Hz. These observations are in agreement with that in the literature. The EEG electrodes F3/F4, Fz and Cz were identified as such exhibiting the largest signal differences with respect to the participants’ different attention states.

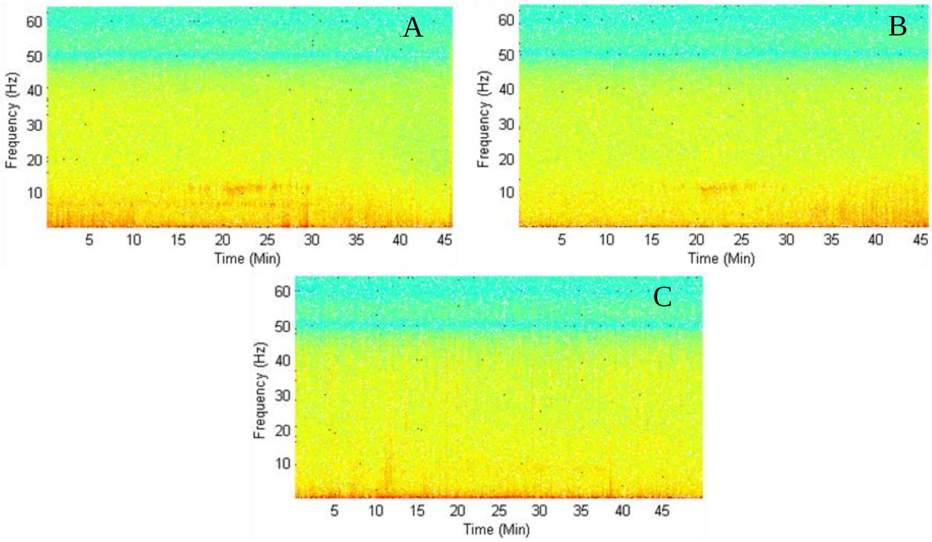

Figure 4. An example of the EEG signal spectrograms obtained in the described experiments, for different EEG channels and different participants. A-B) The examples of the EEG spectrogram observed for the participant S1 in the experiment 1 over the EEG electrodes Fz and Pz, respectively. Note the variation of the EEG signal with respect to the EEG electrode’s position. C) The example of the EEG spectrogram observed for the participant S2 in the experiment 1 over the EEG electrode Fz. Note the variation of the EEG signal with respect to a different participant. The difference in the EEG spectra associated with different attention states during the time-intervals of 0-10 min (initial focused state), 10-20 min (unfocused state), and 20-35 min (drowsy state) are also seen.

Following the preliminary examination, we trained and tested the automatic attention state detection system, as described in Section 2. The performance results of that system are shown in Table 1. Generally, our system showed the ability to correctly detect the participants’ attention states with the accuracy 85-95%. We found that our attention state detection system had to be trained or calibrated for each participant individually, and only after that it could be used to identify the attention states of that individual. In the "generic" version of the above attention state detection system, which was trained jointly using the EEG data from all participants in mixed form, the system failed to show satisfactory discrimination ability, Table 2. These results were obtained either when using the raw EEG data or when the EEG data were "standardized" to have the same mean and variance before processing.

Table 1. Cross-validation accuracy of the attention state detections in the individually trained operator attention state detection system, where the system was trained and used for each participant individually, and the virtual low-intensity control task described.

Subject	Exp1	Exp2	Exp3	Exp4	Exp5	Average
S1	**90%**	**87%**	**91%**	**90%**	**88%**	**89.7%**
S2	**98%**	**99%**	**93%**	**95%**	**97%**	**96.7%**
S3	**88%**	**88%**	**88%**	**86%**	**91%**	**88.6%**
S4	**91%**	**95%**	**92%**	**96%**	**92%**	**93.5%**
S5	**90%**	**81%**	**93%**	**91%**	**93%**	**90.1%**

Table 2. Cross-validation accuracy of the attention state detections in the generic operator attention state detection system, where the system was trained using the mixed data from all participants, and the virtual low-intensity control task described.

Subject	Exp1	Exp2	Exp3	Exp4	Exp5	Average
S1	**81%**	**72%**	**72%**	**74%**	**76%**	**75.0%**
S2	**75%**	**70%**	**71%**	**75%**	**68%**	**71.8%**
S3	**82%**	**68%**	**76%**	**77%**	**72%**	**75.0%**
S4	**79%**	**80%**	**78%**	**79%**	**78%**	**78.8%**
S5	**76%**	**69%**	**74%**	**72%**	**73%**	**72.2%**

To gain an insight about what features of the EEG signal were the most crucial for the detection of the participants' attention states, we examined the weight vectors w produced by the SVM classifiers in our system. An example of such weight vectors w for the three most prominent EEG channels is shown in Fig. 5. In agreement with the general observations above, the SVM classifier for the "focused" state appears to treat the EEG activity in the frequency band 1-5 Hz as a positive evidence towards the "focused" state, Fig. 5A. At the same time, the activity in the frequency band 8-15 Hz is associated with the negative contributions to the classifier's output. For the "unfocused" state, we observe negative contributions to the SVM classifier over essentially all EEG frequencies, indicating that inattentive participants' state is associated with a drop in all EEG activity, across the entire EEG spectrum, Fig. 5B. Finally, the SVM weights for the "drowsy" state show a clear peak at the frequency band of 10-15 Hz, indicating that the alpha-band activity is considered as the indicator of the participants' drowsiness, Fig. 5C.

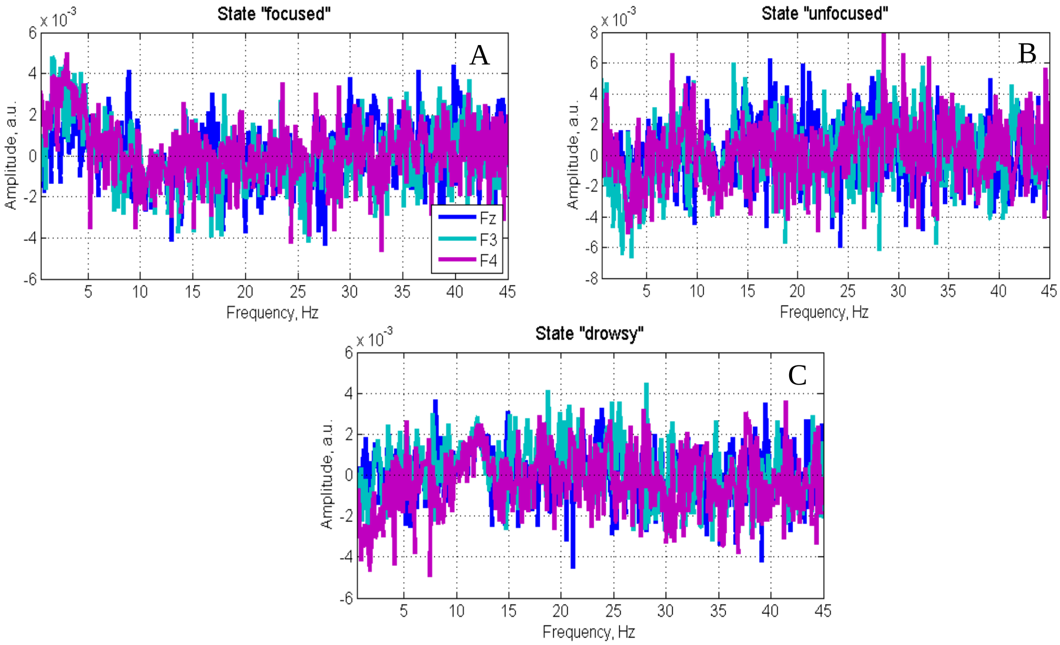

Figure 5. The typical weight-vectors *w* obtained from the SVM classifiers for the attention state detection in our system. Shown are the weight vectors obtained for the participant S1 and three most distinctive EEG channels F3, F4 and Fz, for the SVM classifiers sensitive to the "focused", "unfocused" and "drowsy" attention states, respectively. The legend shown is for all figures.

In order to gain an insight about the relative importance of different EEG channels for the identification of operators' attention state, we evaluated the contribution of each EEG channel to the performance of our system separately. Since the complexity of an EEG device and the inconvenience of using it are directly related to the number of the EEG electrodes, the question of the least number of electrodes necessary for a reliable attention state detection is also important.

Specifically, we used the backward feature elimination procedure to provide an answer to these questions. First, we trained the attention state classifiers using the data from all electrodes and quantified the performance as an average over all participants, whereas however for each participant the training was still done individually. Then, we removed one electrode at a time from the dataset and re-trained and re-evaluated the average performance of the attention state detection system. The electrode with the least impact on the attention state detection performance was thus permanently removed from the dataset and the procedure was repeated until only one electrode remained. The resulting graph of the performance of the attention state detection system versus the number of the electrodes is shown in Fig. 5.

Using the above electrode elimination process, the electrodes in relation to their importance for the attention state detection were ordered as follows: F3-Fz-Cz-F4-Pz-C4-C3, in the order of decreasing importance. Four electrodes, F3/F4, Fz and Cz, were found to contribute the most to the attention state detection and, together, were found to achieve the attention state classification with the accuracy above 85%. Three electrodes, F3, Fz and Cz, could provide the discrimination accuracy of 80-85% and the 2 electrodes, F3 and Fz, could provide the attention state discrimination accuracy of 70-80%, which was not found to be satisfactory.

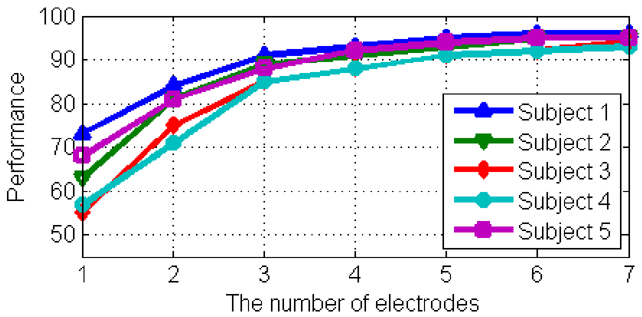

Figure 6. The accuracy of the attention state detections as a function of the number of EEG electrodes used in the dataset. One and two electrodes are found to be insufficient for satisfactory discrimination of the attention states. Three to four electrodes are fond to be sufficient for detection of the attention states with accuracy of 80-90%.

4. Discussion

In this work we discuss an EEG BCI-based system for monitoring the attention state of a general process or system operator engaged in a low-intensity or passive control task. Due to the low cognitive demand of such tasks, they present a significant risk of the operators losing alertness over time, thus, becoming unable to adequately react to emergency situations.

Among the existing techniques with a bearing on that topic, predominant attention in the literature had been given to the detection of drowsiness in car drivers. A variety of systems with such purpose had been discussed in the literature, including monitoring of video imagery, driving patterns, and physiological features of car drivers. Unfortunately, the majority of such systems cannot be readily transferred to the problem of operator's state detection in low-intensity control tasks. The design of many such systems is specific to the driving activities and relies on the specifics of the drivers engaging with their vehicles during driving. This motivates us to investigate the design of a system for detecting the attention state of already predominantly passive operator specifically in the context of a low-intensity system or process control task.

In this work our focus is on the EEG-based operator attention state detection system. Such system has the advantage of the EEG-signal being directly related to the operators' mental activity. An EEG-based system can be straightforwardly generalized to different operational settings, including that of the control of automated assembly lines, industrial processes, video-room supervising, or controlling robotic or autonomous vehicles.

EEG BCI systems are difficult to employ in practical settings due to their susceptibility to mechanical motion and electromagnetic noise as well as muscular EMG signals. These are explicitly attenuated in the context of low-intensity control tasks, where the operator is already predominantly passive and where the electromagnetic interference can be reduced to a minimum within practical means.

We construct a set of machine learning classifiers trained to detect operator's attention states from the EEG signal, and test that system in a specific low-intensity virtual control task, such as that of driving a train on a 35 to 55 minutes long route segment. We find that the patterns in the EEG data associated with different operators' different cognitive states vary among individuals. Thus, our system is trained individually for each operator. Once thus calibrated, however, the system shows the detection accuracies close to 90%. The most important contributors to the attention state discrimination are found to be the EEG channels F3/F4, Fz and Cz and the EEG frequencies 1-5 Hz and 10-15 Hz.

Acknowledgements

This project had been supported by TUBITAK ARDEB grant number 113E611and The Science Academy-Bilim Akademisi young investigator award under the BAGEP program.

References

[1] Lin, C. T., Wu, R. C., Liang, S. F., Chao, W. H., Chen, Y. J., & Jung, T. P. (2005). EEG-based drowsiness estimation for safety driving using independent component analysis. Circuits and Systems I: Regular Papers, IEEE Transactions on, 52(12), 2726-2738.

[2] Li, Y., Li, X., Ratcliffe, M., Liu, L., Qi, Y., & Liu, Q. (2011, September). A real-time EEG-based BCI system for attention recognition in ubiquitous environment. In Proceedings of 2011 international workshop on Ubiquitous affective awareness and intelligent interaction (pp. 33-40).

[3] Hsieh, H. Y., Liang, S. F., Ko, L. W., Lin, M., & Lin, C. T. (2006). Development of a real-time wireless embedded brain signal acquisition/processing system and its application on driver's drowsiness estimation. In Systems, Man and Cybernetics, 2006. SMC'06. IEEE International Conference on (Vol. 5, pp. 4374-4379).

[4] Lin, C. T., Wu, R. C., Jung, T. P., Liang, S. F., & Huang, T. Y. (2005). Estimating driving performance based on EEG spectrum analysis. EURASIP Journal on Applied Signal Processing, 2005, 3165-3174.

[5] Mardi, Z., Ashtiani, S. N. M., & Mikaili, M. (2011). EEG-Based Drowsiness Detection for Safe Driving Using Chaotic Features and Statistical Tests. Journal of medical signals and sensors, 1(2), 130.

[6] Lee, B. G., Jung, S. J., & Chung, W. Y. (2011). Real-time physiological and vision monitoring of vehicle driver for non-intrusive drowsiness detection. IET communications, 5(17), 2461-2469.

[7] Reddy, B. S., Basir, O. A., & Leat, S. J. (2007, June). Estimation of driver attention using Visually Evoked Potentials. In Intelligent Vehicles Symposium, 2007 IEEE (pp. 588-593). IEEE.

[8] Resalat, S. N., Saba, V., & Afdideh, F. (2012, May). A novel system for driver's sleepiness detection using SSVEP. In Artificial Intelligence and Signal Processing (AISP), 2012 16th CSI International Symposium on (pp. 343-347). IEEE.

[9] Ji, H., Li, J., Cao, L., & Wang, D. (2012). A EEG-Based Brain Computer Interface System towards Applicable Vigilance Monitoring. In Foundations of Intelligent Systems Springer Berlin Heidelberg. (pp. 743-749).

[10] Li, J., Yan, C. G., Xia, B., Cao, L., Wang, D. M., & Sun, Y. R. (2010). EEG-based Brain Computer Interface for Vigilance Analysis and Estimate. In Conference on Asia-Pacific Signal and Information Processing Association, APSIPA ASC.

[11] Hashemi, A., Saba, V., & Resalat, S. N. (2014). Real Time Driver's Drowsiness Detection by Processing the EEG Signals Stimulated with External Flickering Light. Basic and Clinical Neuroscience, 5(1), 22-27.

[12] Deshmukh, M. P., Somani, M. S., Mishra, M. S., & Soni, M. D. (2012). EEG BASED DROWSINESS ESTIMATION USING MAHALANOBIS DISTANCE. International Journal of Advanced Research in Computer Science and Electronics Engineering (IJARCSEE), 1(6), pp-104.

[13] Murthy, G. N., & Khan, Z. A. (2014). Cognitive attention behaviour detection systems using Electroencephalograph (EEG) signals. Research Journal of Pharmacy and Technology, 7(2), 238-247.

[14] Borghini, G., Astolfi, L., Vecchiato, G., Mattia, D., & Babiloni, F. (2012). Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness. Neuroscience & Biobehavioral Reviews.

[15] Cao, L., Li, J., Sun, Y., Zhu, H., & Yan, C. (2010, December). EEG-based vigilance analysis by using fisher score and PCA algorithm. In Progress in Informatics and Computing (PIC), 2010 IEEE International Conference on (Vol. 1, pp. 175-179).

[16] Yu, H., Lu, H., Ouyang, T., Liu, H., & Lu, B. L. (2010, August). Vigilance detection based on sparse representation of EEG. In Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE (pp. 2439-2442).

[17] Touryan, J., Apker, G., Lance, B. J., Kerick, S. E., Ries, A. J., & McDowell, K. (2014). Estimating Endogenous Changes in Task Performance from EEG. Neuroprosthetics, 8, 155.

[18] Wan, Z., He, J., & Voisine, A. (2013). An Attention Level Monitoring and Alarming System for the Driver Fatigue in the Pervasive Environment. In Brain and Health Informatics Springer International Publishing. (pp. 287-296).

[19] Wang, F., Wang, S., Wang, X., Peng, Y., & Yang, Y. (2014, May). Design of driving fatigue detection system based on hybrid measures using wavelet-packets transform. In Robotics and Automation (ICRA), 2014 IEEE International Conference on (pp. 4037-4042).

[20] Saini, V., & Saini, R. (2014). Driver drowsiness detection system and techniques: a review. International Journal of Computer Science and Information Technologies, 5(3), 4245-4249.

[21] Baulk, S. D., Reyner, L. A., & Horne, J. A. (2001). Driver sleepiness-evaluation of reaction time measurement as a secondary task. SLEEP-NEW YORK-, 24(6), 695-702.

[22] Torsvall, L. (1987). Sleepiness on the job: continuously measured EEG changes in train drivers. Electroencephalography and clinical Neurophysiology, 66(6), 502-511.

[23] Baulk, S. D., Reyner, L. A., & Horne, J. A. (2001). Driver sleepiness-evaluation of reaction time measurement as a secondary task. SLEEP-NEW YORK-, 24(6), 695-702.

[24] Simon, M., Schmidt, E. A., Kincses, W. E., Fritzsche, M., Bruns, A., Aufmuth, C., ... & Schrauf, M. (2011). EEG alpha spindle measures as indicators of driver fatigue under real traffic conditions. Clinical Neurophysiology, 122(6), 1168-1178.

[25] Yeo, M. V., Li, X., Shen, K., & Wilder-Smith, E. P. (2009). Can SVM be used for automatic EEG detection of drowsiness during car driving?. Safety Science, 47(1), 115-124.

[26] Suykens, J. A. K., Lukas, L., Van Dooren, P., De Moor, B., & Vandewalle, J. (1999, September). Least squares support vector machine classifiers: a large scale algorithm. In European Conference on Circuit Theory and Design, ECCTD (Vol. 99, pp. 839-842).

[27] Almeida, L. B. (1994). The fractional Fourier transform and time-frequency representations. Signal Processing, IEEE Transactions on, 42(11), 3084-3091.

[28] Lobos, T., & Rezmer, J. (1997). Real-time determination of power system frequency. Instrumentation and Measurement, IEEE Transactions on, 46(4), 877-881.

[29] Wolpaw, Jonathan R., et al. "Brain-computer interface technology: a review of the first international meeting." IEEE transactions on rehabilitation engineering 8.2 (2000): 164-173.