Expert Systems With Applications 134 (2019) 153–166

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Distinguishing mental attention states of humans via an EEG-based passive BCI using machine learning methods

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ARTICLE INFO

Article history:
Received 30 January 2019
Revised 13 May 2019
Accepted 30 May 2019
Available online 30 May 2019

Keywords:
EEG
BCI
Mental state detection
Drowsiness detection
Support vector machine
Passive control task

ABSTRACT

Recent advances in technology bring about novel operating environments where the role of human participants is reduced to passive observation. While opening new frontiers in productivity and lifestyle, such environments also create hazards related to the inability of human individuals to maintain focus and concentration during passive control tasks. A passive brain-computer interface for monitoring mental attention states of human individuals (focused, unfocused, and drowsy) by using electroencephalographic (EEG) brain activity imaging and machine learning data analysis methods is developed in this work. An EEG data processing pipeline and a machine learning mental state detection algorithm using the Support Vector Machine (SVM) method were designed and compared with k-Nearest Neighbor and Adaptive Neuro-Fuzzy System methods. To collect 25 h of EEG data from 5 participants, a classic EEG headset was modified. We found that the changes in EEG activity in frontal and parietal lobes occurring at 1–5 Hz and 10–15 Hz frequency bands were associated with the changes in individuals' attention state. We demonstrated the ability to use such changes to identify individuals' attention state with 96.70% (best) and 91.72% (avg.) accuracy in experimental settings using a version of continuous performance task with SVM-based mental state detector. The findings help guide the design of future systems for monitoring the state of human individuals by means of EEG brain activity data.

1. Introduction

Recent advances in automation and robotics bring about new operating environments where the role of human participants is increasingly reduced to passive observation. While opening radically new venues for improvements in productivity and lifestyle, such operating environments also create new hazards related to the inability of human operators to maintain concentration on passive control tasks. One of the best approaches for monitoring the state of human individuals in such circumstances can be expected to be Brain-computer interfaces (BCIs). In this section, the use of BCIs in detection of the driver's mental attention is reviewed, and the motivation of this study is emphasized.

1.1. Literature review

BCIs establish a direct communication channel between a brain and a computer or external device (Shangkai, Yijun, Xiaorong, & Bo, 2014). BCIs offer a novel communication paradigm between human beings and computers that bypass conventional interaction channels such as keyboard input or speech. Non-invasive BCI, namely those that use electroencephalography (EEG), magnetoencephalography, or magnetic resonance imaging to observe brain activity, are of special interest for addressing the problem of observing the mental state of human individuals by directly monitoring their brain activity, thus avoiding the pitfalls of less direct methods (Myrden & Chau, 2017). The use of EEG in this regard is of special interest given the established nature of EEG technology, the relative ease of use of modern EEG headsets, as well as the small size, cost, portability, and reliability of existing modern EEG solutions (Alirezaei & Sardouie, 2017; Aricò et al., 2016; Resalat & Saba, 2015).

Several studies in the past made use of EEG for fatigue detection in the context of car driving. For instance, Hsieh, Liang, Ko, Lin, and Lin (2006) developed a system that estimates a

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https://doi.org/10.1016/j.eswa.2019.05.057
0957-4174/

vehicle's positioning the lane by using the driver's EEG signals in the context of fatigue detection of car drivers. Yeo, Li, Shen, and Wilder-Smith (2009) reported a connection between alerted and drowsy states of car drivers and the changes in the EEG beta and alpha rhythms. They subsequently proposed a system to automatically detect the onset of fatigue of car drivers as well as to test such a system in simulated and real driving conditions. Mardi, Ashtiani, and Mikaili (2011) studied the association between drowsiness and certain chaotic features of EEG signals for a similar purpose of fatigue detection. Simon et al. (2011) studied the possibility of sleepiness detection of car drivers again by means of EEG alpha spindles. They demonstrated that changes in the parameters of alpha spindles in the EEG signals can be associated with the increase of the drivers' fatigue. Hashemi, Saba, and Resalat (2014) developed a Steady State Visually Evoked Potential EEG BCI for detecting the onset of drowsiness of car drivers.

A few studies reported applications of EEG BCI for the discovery of subjects' mental states in settings different from car driving: Borghini, Astolfi, Vecchiato, and Mattia (2014) examined the correlation between mental workload and EEG signals under different conditions such as those of airplane pilots or car drivers. Arico et al. (2017) developed a passive EEG BCI for the assessment of mental workload of air traffic controllers. A study by Myrden and Chau (2017) described a passive EEG BCI for detecting changes in fatigue, frustration, and attention states during mental workload tasks including mental arithmetic, anagram solution, and short-term memory recall.

The data generated by the studies of determining the mental states of humans using EEG recordings led researchers to estimate the mental state by using these datasets and machine learning methods: Li et al. (2011) classified three attention levels by a k-Nearest Neighbor (kNN) classifier based on the Self-Assessment Manikin mode. Subjects were given several mental tasks to undertake and asked to report on their attention level during the tasks using a set of attention classifications. The average accuracy rate is shown to reach 57.03% after seven sessions of EEG training. In the study of Liu, Chiang, and Chu (2013), whether students were attentive or inattentive during instruction was determined by observing their EEG signals. A Support Vector Machine (SVM) classifier was used to calculate and analyze these features to identify the combination of features that best indicated whether students were attentive. Their method provided a classification accuracy of up to 76.82%. Lee et al. (2014) developed a driver monitoring system that classifies driving mental fatigue condition by analyzing EEG and respiration signals of a driver in the time and frequency domains. Test results revealed that the combined use of the EEG and respiration signals resulted in 98.6% recognition accuracy. Although the result is promising, Lee et al.'s system needs the respiration data of the driver as well as EEG signals. Ke et al. (2014) carried out two experiments where all subjects were instructed to perform tasks with three different attention levels (i.e. attention, no attention and rest). Then, statistical analyses and classification with SVM were performed. They obtained results with the accuracies of 76.19% and 85.24% in recognition of three levels of attention for the two experiments, respectively. Wang, Jung, and Lin (2015) developed a countermeasure to track drivers' focus of attention and engagement of operators in dual (multi)-tasking conditions using SVM. The system achieved $84.6 \pm 5.8\%$ and $86.2 \pm 5.4\%$ classification accuracies in detecting the participants' focus of attentions on math and driving tasks, respectively. In another study performed by Djamal, Pangestu, and Dewi (2016), attention and inattention states were recognized using wavelet filter and SVM. They experimented with four subjects and achieved an accuracy of 77–83%. In the study of Nuamah and Seong (2018), task engagement indices of the five cognitive tasks were used as inputs to SVM. The average classification accuracy across the six participants was $93.33 \pm 8.16\%$. They achieved very good results due to the differences in cognitive task demand between six different tasks.

1.2. Motivation of the study

In this paper, we studied the problem of detecting mental state changes in human individuals who need to remain dormant or passive while also having to maintain a continuous significant level of concentration or attention. An example of such a scenario can be supervising automated processes or systems. Another example can be controlling robotic vehicles or drones or security monitoring. Yet another example can be long-term monitoring of aircraft pilots while under the control of the autopilot. In all these cases, non-interfering supervision of processes is desired, while also alertness and a quick reaction is required of the involved individuals.

With this study, we aimed to demonstrate that it is possible to identify pure mental states such as engaged and focused attention versus detached and unfocused monitoring from EEG data and tried to develop a machine learning-based system for solving such a task. Previous studies have used extra data (e.g., task engagement index or respiration data) to support EEG signals or limited the number of mental states detected to two to achieve high accuracy. We tried to detect the differentiation of engaged / focused, detached / unfocused, and drowsing mental states experimentally in a version of continuous performance tasks with 96.70% (best) and 91.72% (avg.) accuracies by using only the EEG data. The approach to the subjects' state detection used in this study is generally accepted and therefore can easily be generalized in the future related to the development of subject state monitoring systems in different settings such as patients' state monitoring in hospitals, as well as helping improve safety mechanisms of modern automated and robotic systems.

We emphasize that, although the paper makes use of well-established signal processing and data analysis techniques, the topic of application of such techniques for the identification of mental states of the brain's activity, including "pure" mental states that have not been externally manifested in a clear way, is novel. The identification of the passively disengaged state is of high relevance to control/passive supervision processes and is, as far as is known, the first study in the literature. Similarly, the identification of attention states of passive subjects is also the first study of that kind in the literature – previous works focused on monitoring the states of car drivers and similar operators who are continuously active by the nature of that setup. Such settings are considerably different from identifying drowsiness or detachment of subjects who are permanently passive. The general approach used to solve this problem here, namely using samples of EEG data obtained for self-identified mental states of subjects and machine learning, is highly general and can be applied to the investigation of other mental states, including the pure mental states, which is also a novel point of view in the literature.

2. Material and method

2.1. Experimental procedure

In this study, an original dataset that comprised a total of 25-hour EEG recordings collected from 5 participants engaged in a low-intensity control task was used. The task consisted of controlling a computer-simulated train using the "Microsoft Train Simulator" program. Each experiment consisted of the participants controlling a train for 35 to 55 min over a primarily featureless route in the above-mentioned computer simulation program.

The 3 mental states examined in this study included the focused but passive attention, the unfocused or detached but awake state and the drowsing state. The first, "focused" state, was

Fig. 1. The organization of the continuous performance task based on a virtual passive control task used in this work.

understood to correspond to passively supervising the train while maintaining focus and concentration. Active engagement was not implied in this state. In fact, most of the task did not involve active intervention into the travel on the part of the participants. Nonetheless, continuous concentration and focus were required.

The second state was that of disengaged supervision, detached but awake, where the participants did not explicitly drowse, yet stopped paying attention to the developments on the screen and being alert. One can interpret this as a dangerous state that should be detected and produce an alert, should it be realized. On the other hand, such a state may not be manifested clearly via any external cues and may be difficult to detect, such as by using video monitoring. We can call such a state "pure", in that it is performed mentally but without necessarily any clear external signatures. The methodology for the discrimination of such states is among the main objectives of this study.

The third state was that of explicit drowsing. As described in the introduction, drowsing was previously associated with increased alpha-band EEG activity, and its detection by the EEG data was already discussed in the literature. At the same time, drowsiness can also be detected via non-EEG means, such as by monitoring eyelids in a video or by heart rate monitoring.

In the context of detecting the above-mentioned 3 mental states, the participants simulated those states during each experiment, following instructions of the experiment's supervisor, which they received at the beginning of each experiment. Participants controlled a simulated passenger train over a primarily featureless route for a duration of 35 to 55 min. Specifically, during the first 10 min of each experiment, the participants were engaged in focused control of the simulated train, paying close attention to the simulator's controls, and following the developments on the screen in detail. During the second 10 min of the experiments, the participants stopped following the simulator and became de-focused. The participants did not provide any control inputs during that time and stopped paying attention to the developments on the computer screen; however, they were not allowed to close their eyes or drowse. Finally, during the third 10 min of the experiments, the participants were allowed to relax freely, close their eyes and doze off, as desired (Fig. 1).

Specific settings of the train control simulation experiments included using the "Acela Express" modern locomotive and a 40-minute segment of the "Amtrak-Philadelphia" route in the above-mentioned train simulator program. The segment of the route chosen for simulations was flat and featureless so that the participants had to provide little control inputs during the simulations with the exception of the initial and the final 5-minute segments of the route, where a higher level of involvement was necessary. The participants were instructed to maintain the speed of the simulated train at a steady 40 mph in all experiments. The controls consisted of the throttle adjustment (controlling the travel speed) and the brake application (to produce a rapid deceleration). The controls were enacted via keys on a standard computer keyboard.

Each participant took part in 7 experiments, performing at most one experiment per day. The first 2 experiments were used for habituation, and the last 5 trials were used for collecting the data. All experiments were conducted between the evening hours of 7 pm and 9 pm to facilitate the participants entering the drowsy state during the 3rd phase of the trials. The participants were monitored by the experiment's supervisor and recorded on a video to ensure that the experiments complied with the above-stated structure and that no significant disruptions, such as moving or talking, took place.

As well as the raw data of the experiments is available to the researchers on the Kaggle website (Acı, Kaya, & Mishchenko, 2019), an actual data snippet is given in Table 1.

2.2. EEG headset modification

The EEG data was acquired using a modified Epoc EEG headset and its classic wet electrodes. The Epoc headset is a portable EEG acquisition device providing 12 channels real-time EEG data at a sampling rate of 128 Hz, a voltage resolution of 0.51 μV, and a bandwidth between 0.2–43 Hz, connecting to a data-acquisition computer via a wireless Bluetooth link (EPOC+, 2019). We modified the headset to allow the electrodes to be placed over frontal and parietal lobes of the scalp (Fig. 2), whereas the original Epoc headset only allowed electrode coverage over frontal and occipital areas within a rigid plastic spider-web cap format. Thus, the positions of the electrodes used in this work were F3-Fz-F4-C3-Cz-C4-T3-T4-T5-T6-Pz in the standard 10–20 system. In the EEG device, 4 leads (here identified by the locations T3, T4, T5, and T6) were used to supply current and establish the EEG reference and could not be used for data collection. The acquired data from the 7 leads were identified by F3, F4, Fz, C3, C4, Cz, and Pz. The raw EEG data was acquired from the Epoc device using a custom Matlab script developed based on the sample program *eeglogger.m,* which was shipped with the data-acquisition API in Research License of the Epoc's software. Wet electrodes' impedance was checked at the start and the end of the experiments. If the electrodes' impedance was not at the desired level at the end of the experiment, the experiment was repeated.

Table 1
Sample data.

Cnt.	Intp.	Channel F3	Channel FZ	Channel T3	Channel F4	Channel C3	Channel CZ	Channel C4	Channel T4	Channel PZ	X	Y
80	0	4020.51	4915.90	4036.92	4328.72	4285.13	4035.90	4250.77	4304.62	4102.56	1570	1719
81	0	4021.03	4913.85	4039.49	4329.23	4283.59	4035.90	4250.26	4304.62	4107.18	1569	1720
82	0	4016.41	4909.23	4038.97	4327.69	4277.95	4035.38	4250.26	4304.62	4106.67	1568	1721
83	0	4009.23	4907.69	4036.41	4325.64	4270.77	4028.21	4246.15	4304.62	4105.64	1569	1719
84	0	4003.08	4905.64	4036.41	4326.15	4264.10	4017.44	4245.13	4304.62	4107.18	1568	1722
85	0	3994.36	4902.56	4036.41	4323.59	4255.38	4010.26	4243.59	4304.62	4106.67	1569	1721
86	0	3988.21	4904.10	4034.87	4322.05	4248.72	4006.15	4236.41	4304.62	4106.15	1567	1721
87	0	3988.72	4903.08	4035.38	4324.62	4252.31	4003.08	4234.36	4304.62	4107.69	1568	1722
88	0	3991.28	4902.05	4034.36	4327.18	4258.46	4002.56	4238.46	4304.62	4106.15	1567	1721
89	0	3991.79	4903.08	4034.36	4326.67	4261.03	4000.00	4236.92	4304.62	4101.03	1566	1721
90	0	3991.28	4898.97	4034.36	4325.64	4260.00	3994.87	4232.31	4304.62	4097.44	1566	1720
91	0	3990.77	4893.33	4034.87	4325.64	4255.90	3991.79	4234.36	4304.62	4093.85	1565	1719
92	0	3988.72	4893.85	4035.38	4324.10	4254.87	3991.79	4233.85	4304.62	4090.26	1564	1717
93	0	3988.21	4895.38	4034.36	4322.05	4257.44	3992.31	4230.77	4304.62	4090.77	1563	1717
94	0	3994.36	4894.36	4034.36	4325.64	4261.03	3994.36	4234.87	4304.62	4092.82	1562	1715

Cnt = Sample counter.
Intp. = Indicate if data is interpolated.
X = Gyroscope X-axis.
Y = Gyroscope Y-axis.

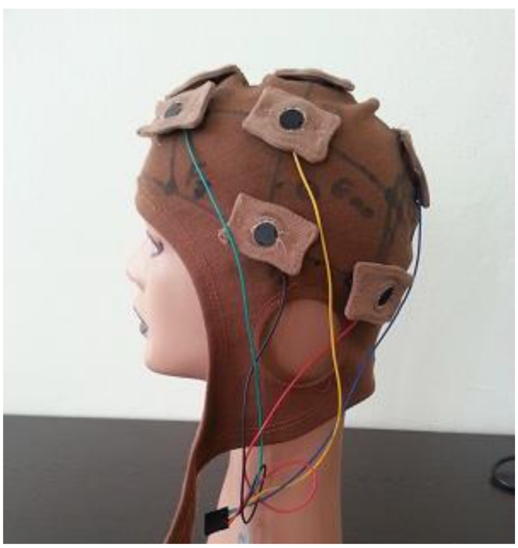

Fig. 2. The modified headset.

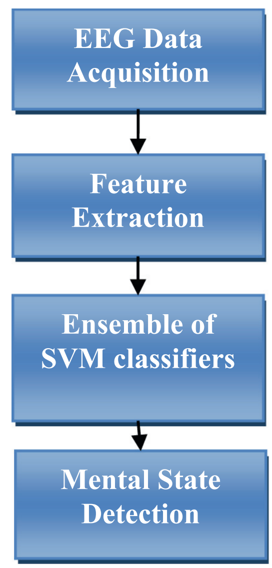

Fig. 3. The block diagram of the mental attention state detector.

2.3. Data preprocessing and feature extraction

We developed an algorithm for detecting the subjects' mental attention states based on the EEG signals represented in the time-frequency domain. The general block diagram of detecting the subjects' mental attention states based on the EEG signals is shown in Fig. 3. During the feature extraction stage, we calculated the spectrograms of the EEG signals in each EEG channel, using the short-time Fourier transform (STFT) and the Blackman window (Almeida, 1994; Lobos & Rezmer, 1997). Briefly, STFT encodes a time-dependent (temporally localized) distribution of the power in the EEG signal frequency spectrum over a small-time interval defined in (1),

$$X_{STFT}(t,\omega) = \sum_{t'=-\infty}^{\infty} x(t')w(t'-t)e^{-j\omega t'} \tag{1}$$

Here, $x(t)$ is the EEG signals in a single EEG channel in the time domain, $w(t)$ is the so-called "windowing" function that differs from zero only in a small neighborhood of $t'=t$ and enforces the localization of EEG signals to a small t'-interval around $t'=t$. The spectrogram is defined as the square of the STFT amplitudes. $S(t,\omega) = |X_{STFT}(t,\omega)|^2$ and quantifies the frequency composition of the EEG signals near a given time point.

The raw EEG data was acquired from the Epoc Emotiv headset in 7 channels at a sampling frequency of $Fs = 128$ Hz. The STFT calculation was performed separately for each channel. STFT was computed using $\Delta T = 15$ second fragments of EEG signals and $m = 1024$ fast discrete Fourier transform (DFT). The Blackman windowing function was used to make the EEG signal taper at both ends of each fragment. The Blackman windowing function is defined by (2).

$$w(\hat{t}) = \begin{cases} 0.42 - 0.5\cos\frac{2\pi\hat{t}}{M-1} + 0.08\cos\frac{4\pi\hat{t}}{M-1}, & 0 \le \hat{t} < M \\ 0, & otherwise \end{cases} \tag{2}$$

where M is the total number of time points within the window ($M = Fs \cdot \Delta T = 1920$) and $\hat{t} = 0,1,\ldots,M-1$ is a discrete time-index within the window. STFT was then calculated at a time step of 1 s producing a set of time-varying DFT amplitudes $X_{STFT}(t,\omega)$ at 1 s intervals within each input EEG channel.

After calculating STFT in each EEG channel, the absolute squares of the DFT amplitudes were calculated to construct the time-dependent power spectrum (that is, spectrogram) of the EEG

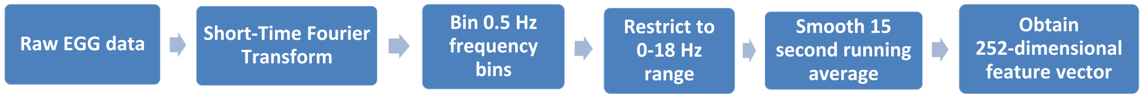

Fig. 4. The block diagram of the feature extraction step.

signal $S(t, \omega)$ in each channel as discussed above. Due to $m = 1024$ points used in DFT, the obtained spectrum characterized the power distribution in the EEG signal over $m/2 + 1 = 513$ frequencies $\omega_k = kFs/m = 0.125k$ Hz, where k changed between 0 and $m/2 = 512$. These were subsequently binned into 0.5 Hz frequency bands by using average, thus, evaluating an average spectral power in each 0.5 Hz frequency band from 0 to 64 Hz. The frequency range was then restricted to 0–18 Hz so that only 36 frequencies, $\Omega_k = k \cdot 0.5$ Hz, $k = 1,...,16$, were retained in the dataset. The constant component $\Omega = 0$ Hz was discarded. Finally, the binned and frequency-restricted spectrograms $S(t, \Omega)$ were temporally smoothed by using a 15 s-running average.

The calculation above produced for each channel smoothed time-dependent power spectra $S(t, \Omega)$ of the EEG signal at frequencies $\Omega_k = k \cdot 0.5$ Hz, $k = 1,...,36$, at 1 s time intervals. The final feature vector was then formed by converting the power values at each time-point t into decibel form and combining the spectra from all 7 input EEG channels into a single, joint feature vector (3);

$$\bar{f}(t) = (10\log_{10} S_c(t, \Omega), c = 1, \ldots, 7, \Omega = k \cdot 0.5 \text{ Hz}, \quad k = 1, \ldots, 36), \tag{3}$$

where c enumerates the input EEG channels.

An important parameter of the feature extraction procedure is the temporal span of the STFT's windowing function $w(t)$ and the width of temporal smoothing. A larger window and wider temporal smoother provide a greater degree of smoothing in the resulting power spectra, thus offering a better noise suppression while sacrificing the temporal resolution and the responsiveness of any possible detector downstream. A smaller window and shorter time smoother offer a higher temporal sensitivity and responsiveness, but at the expense of greater amounts of noise in the STFT amplitudes.

We experimented with different choices of these parameters, considering 1, 5, 15, 30 and 60-s intervals for both the Blackman window and the temporal running filter. 1- and 5-s intervals provided a rapid response to EEG changes. 30- and 60-s intervals provided a greater degree of noise suppression but also incurred 30- to 60-s delay before any changes in the EEG signals could appear in the spectra or affect the detector. We observed that the choice of the 15-s interval for the window size and the running average provided a good compromise between the two effects above and was therefore adopted in this study. The flowchart of the feature extraction step is shown in Fig. 4.

2.4. Mental state detection

We implemented the mental state detector using the machine learning approach of the Least Squares Support Vector Machines (SVM) (Suykens & Vandewalle, 1999). To develop an SVM detector, firstly the spectra of the time-varying EEG signal were reorganized into a feature vector. This was done by combining the power spectra calculated for every time point from all input EEG channels, therefore producing a vector with a dimensionality of 252, characterizing the distribution of the power of the EEG signal over all EEG channels and the frequencies from 0 to 18 Hz at a 0.5 Hz step. After that, an SVM classifier was trained to detect each mental state separately. The training data was composed of a specified number of feature vectors chosen at random time points from the EEG spectral data. As SVM is a two-class classifier, multiple SVM classifiers were required to be combined for the discrimination of more than two mental states. Specifically, the first SVM classifier was trained to detect the occurrence of the "focused" state in the EEG data against all the rest. A second SVM classifier was trained to detect the occurrence of the "unfocused" state against all the rest.

2.5. Design of the SVM classifiers

The SVM classifiers were trained using the *svmtrain* function of the Matlab Statistics Toolbox. The tuning parameters were used as their default values. The *auto-scaling* parameter (reducing the mean and the variance of the training data to zero and one, respectively) was enabled, and *box constraint* (the cost of misclassifications in SVM) was set to 1. The linear kernel function and the "least squares" method were used for solving the SVM optimization problem caused by the large size of the training data involved in this study.

SVM is based on the result of a linear convolution of a feature vector characterizing the temporally-local EEG signal with a vector with weights of W, $y = \sum_i W_i f_i$, where f_i represents the spectral power features and i represents the index enumerating such features as well as the corresponding weights W_i. As the feature vector of each time-point is classified as either +1 (present) if $y \geq b$ over a certain threshold b, or as −1 (absent) otherwise, the sign and the magnitude of the individual weights W_i provide information about the contribution and the importance of each feature to the decision process of the detector. By the construction of the feature vector $\bar{f}(t)$, the weights W_i indicate the frequencies and the electrodes contributing to the discrimination of particular mental states, both in a positive sense when $W_i > 0$ and negative sense when $W_i < 0$.

A plot showing a typical example of the weight vectors W for participant S1 over the three most distinctive EEG channels of F3, F4 and Fz is given in Fig. 5. As can be seen there, the examination of SVM weight vectors indicates that elevated EEG power in the frequency range of 1–5 Hz is treated as a positive evidence of the presence of "focused" state by the detector, while the elevated power in the frequency range of 10–15 Hz is taken as an indication of the "drowsing" state. These observations are in agreement with the results in Section 3, as well as with the findings concerning the EEG signature of drowsy and alert mental states in the literature. The indicator of the "unfocused" or disengaged mental state is the reduction in the EEG power at both 1–5 Hz and 10–15 Hz frequencies (Fig. 5B). This corresponds to the learning of the EEG spectrum in the disengaged mental state.

Consequently, 3 SVM classifiers were developed to classify the "focused", "unfocused", and "drowsing" states in the EEG data. The outputs of the classifiers were combined by using an XOR-aggregation to produce final detections. If any classifier responded with a "+1" (present) at a given time point when the other classifiers responded with a "−1" (absent), then such a time-point was categorized according to the label of the classifier that responded. If two or more classifiers responded with a "+1" or all classifiers responded with a "−1", then such a time point was categorized as "unclassified" and became an error.

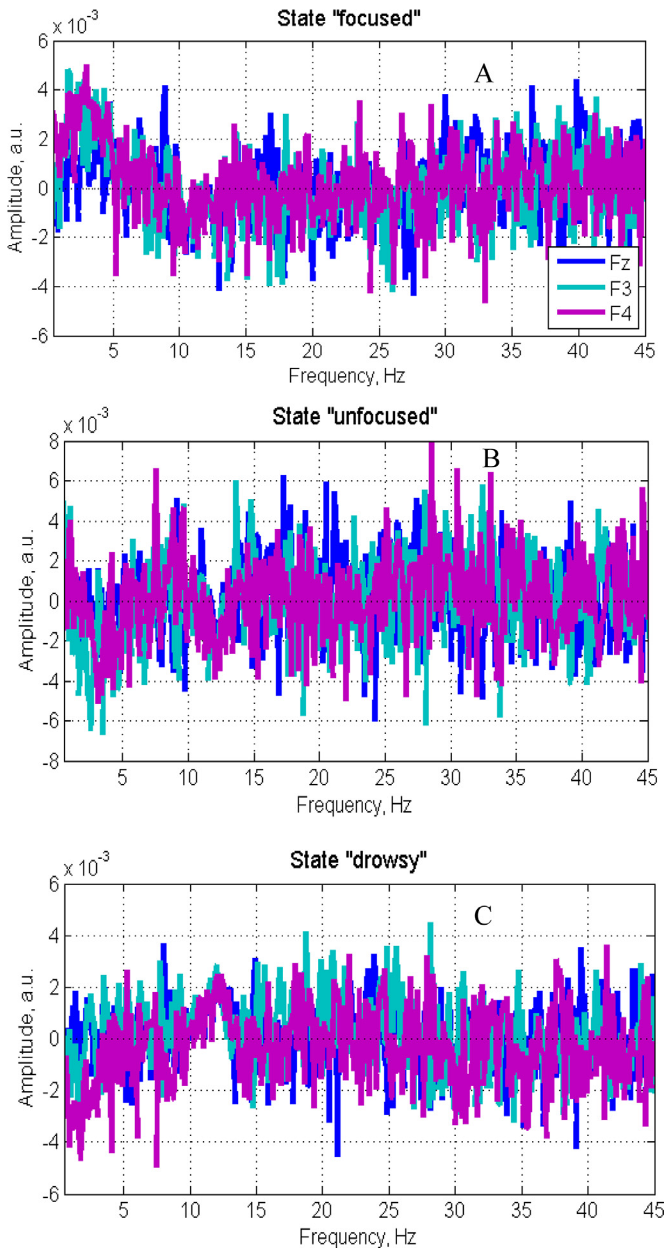

Fig. 5. An example of SVM weight vectors for focused (A), unfocused (B) and drowsing (C) mental states.

2.6. Performance evaluation

The performance of the SVM-based mental state detector is evaluated using random hold-out cross-validation. Cross-validation is a standard approach for evaluating the accuracy of classification and regression models in machine learning. In cross-validation, a subset of available data is withheld from training so that the machine learning model cannot see that data or have the knowledge of the information contained in the withheld dataset. After the training has finished, using whichever machine learning algorithm, an unbiased estimate of the performance of the final model was obtained by applying it to the withheld validation dataset and evaluating the accuracy of the model there. In random hold-out cross-validation, a certain percentage of randomly chosen data points was chosen and withheld prior to training and, subsequently, used for evaluation of the accuracy of the final detector.

Here, two evaluation paradigms (i.e. subject-specific and common-subject) were evaluated: In the subject-specific paradigm, the mental state detector was trained individually for each participant based on the data collected for that participant only. 80% of random time points from the EEG data from all experiments of that individual were used for training the SVM state-classifiers. The accuracy of the produced individual detector was then evaluated on the remaining 20% of the data of all trials that was not used in the training. Here, the training data of each participant generally consisted of 6000 data points randomly pulled together from different trials of the same subject. Respectively, 1500 data points were used for the evaluation of the performance of the final detector. In this approach, a different mental state detector was trained for each participant.

In the case of the common-subject paradigm, a single detector was jointly trained for all participants. 80% of the data from all joint EEG recordings of all participants was randomly selected for training. The performance of the “mixed” or “generic” detector was then evaluated against the dataset of mixed data, as well as against the data of each participant individually, which was not seen in the training. The cross-validation here was performed both jointly for all participants and individually for each participant to obtain the goodness of the generic mental state detector both overall, as well as on per-participant basis.

3. Results

All experiments in this study were performed with healthy volunteer participants chosen among students. All participants signed the informed consent form after receiving the instructions about the objectives and procedures of the experiments.

Fig. 6 shows a sample EEG data before the SVM-based classifier training part. The differences in the EEG signals associated with the different attention states can be seen in the spectrograms. Red dashed lines indicate the different attention state periods corresponding to the time-intervals of 0–10 min (focused), 10–20 min (unfocused), and 20–35 min (drowsy).

The preliminary examination of the collected data revealed that the changes in the individuals’ attention states could be related to the changes in the EEG spectral power distribution, appearing as changes at certain frequencies in certain EEG channels. The varying composition of EEG signals with respect to the location of the electrodes can be seen in Fig. 7. In the figure, sections (A) and (B) show sample EEG spectrograms collected during the continuous performance task from the EEG electrodes Fz (A) and Pz (B) for participant S1. Section (C) indicates EEG spectrogram collected for participant S2 from the electrode Fz.

More specifically, focused and unfocused attention states appeared to be associated with enhanced or suppressed EEG activity at 1–10 Hz frequency bands in the frontal EEG channels F3, F4, and Fz. The drowsing state could be observed as continuous or intermittent power spouts at alpha-band frequency in the EEG signals at 10–15 Hz and the EEG channels C3, C4, Cz, and Pz. This examination suggests that focused, unfocused, and drowsing states of the participants could be distinguished in the EEG data based on the local spectrum of the signal in various EEG channels.

We then constructed an SVM-based algorithm for the detection of the above mental states from the EEG data, as described in Section 2.5. The examination of the spectral power features in such a detector supported the preliminary observations above. In particular, Table 2 lists some of the features of the mental state detector and its statistical properties, organized according to the Intra class Correlation Coefficient (ICC) of such features with the target detector states. ICC is a statistical measure of relatedness of a continuous predictor variable with a discrete outcome variable,

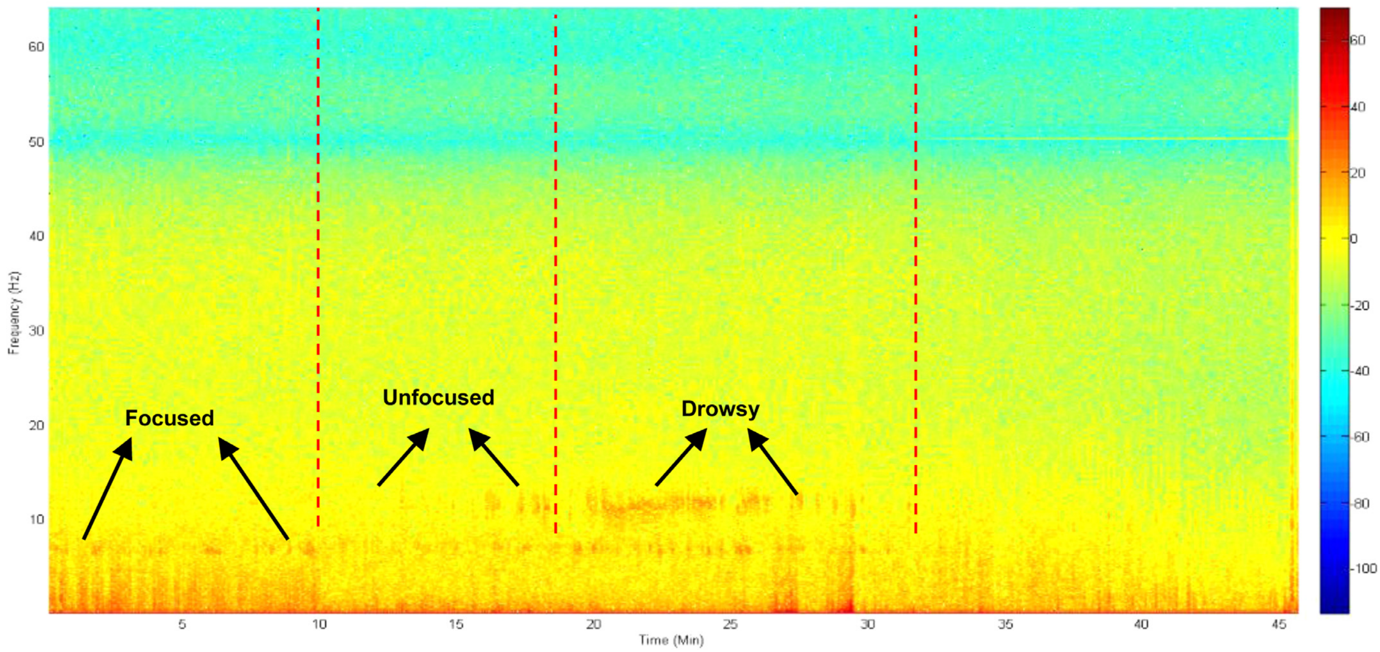

Fig. 6. A sample EEG data before the SVM-based classifier training part.

Table 2
Statistical properties of the 25 most significant features based on the ICC with the target mental state variable.

Rank	Channel	Frequency (Hz)	Mean	STD	Mean focused	Mean unfocused	Mean drowsy	ICC
1	C3	12	7.3701	6.6015	3.0069	2.8568	15.258	0.77489
2	F3	12	7.3351	7.1219	2.6434	2.4826	15.817	0.76973
3	C4	12	7.0274	6.9183	2.5108	2.2899	15.251	0.76694
4	Cz	12	7.1504	6.9895	2.5024	2.4753	15.436	0.76248
5	F4	12	7.7564	6.9367	3.2259	3.0626	15.954	0.75787
6	C3	11.5	7.2411	6.4331	2.6736	3.2756	14.824	0.75544
7	C4	11.5	6.8756	6.5842	2.2998	2.7417	14.616	0.75063
8	F3	11.5	7.1857	6.7928	2.3314	3.0661	15.161	0.74986
9	Pz	12	5.6787	5.9377	2.0338	1.5049	12.627	0.74438
10	Fz	12	6.24	7.2337	1.4592	1.4907	14.709	0.7438
11	F4	11.5	7.5599	6.7017	2.8145	3.5413	15.348	0.73483
12	Cz	11.5	7.0045	6.7105	2.3403	2.8885	14.807	0.73479
13	Fz	11.5	6.1487	7.0016	1.181	2.1192	14.144	0.71065
14	Pz	11.5	5.866	6.0477	1.9401	2.0206	12.772	0.70766
15	C4	12.5	5.9152	6.233	1.9	1.9717	12.988	0.6987
16	F3	12.5	6.3208	6.3337	2.2655	2.2949	13.502	0.69763
17	C3	12.5	6.2436	5.8986	2.4349	2.5351	12.924	0.69603
				…				
43	F4	3	10.72	3.4544	14.252	9.0921	9.0286	0.50204
44	F4	3.5	9.5554	3.2217	12.813	8.2334	7.8354	0.49144
45	F4	2.5	11.889	3.4799	15.402	10.138	10.323	0.49129
46	F4	4	8.86	3.049	11.921	7.5095	7.3397	0.48387
47	F4	4	8.1726	2.8992	11.054	6.8883	6.7534	0.47408
48	F4	2.5	11.351	3.2627	14.548	9.691	9.9839	0.46457
				…				

related to the simple Pearson correlation, and defined by (4)

$$ICC = \frac{variance\ of\ group\ means}{full\ variance} \tag{4}$$

Table 2 shows two types of differences in the EEG signals associated with different mental attention states – an increase in alpha band power at frequencies 8–13 Hz, especially over the parietal lobe (electrodes C3, C4, Cz and Pz), and a decrease at lower delta and theta band frequencies 1–4 Hz, especially over the frontal lobe (electrodes F3, F4 and Fz).

The performance of the SVM-based mental state classifier is evaluated in terms of the rate of accuracy measure given by (5).

$$Accurracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \tag{5}$$

Tables 3 and 4 show the accuracy results of the SVM-based mental state classifier for subject-specific and common-subject paradigms, respectively. As can be seen from the tables, we succeeded in distinguishing the mental attention states for all participants in the subject-specific paradigm with an average accuracy ranging from 88.60 to 96.70%. The identification of mental states for the common-subject paradigm could be achieved at 71.80 to 78.80% accuracy.

To demonstrate the efficiency of the results obtained from the SVM-based classifier, the mental attention states were classified by

Table 3
The accuracy results of the attention state for the subject-specific paradigm with SVM using 7 electrodes.

Subject	Fold #1	Fold #2	Fold #3	Fold #4	Fold #5	Average of five folds
S1	98%	**99%**	93%	95%	97%	**96.70%**
S2	90%	87%	91%	90%	88%	89.70%
S3	88%	88%	88%	86%	91%	88.60%
S4	91%	95%	92%	96%	92%	93.50%
S5	90%	81%	93%	91%	93%	90.10%

Table 4
The accuracy results of the attention state for the common-subject paradigm with SVM using 7 electrodes.

Subject	Fold #1	Fold #2	Fold #3	Fold #4	Fold #5	Average of five folds
S1	75%	70%	71%	75%	68%	71.80%
S2	81%	72%	72%	74%	76%	75.00%
S3	82%	68%	76%	77%	72%	75.00%
S4	79%	80%	78%	79%	78%	78.80%
S5	76%	69%	74%	72%	73%	72.20%

Table 5
Comparison of average 5-fold cross validation results of Machine Learning methods for subject-specific paradigm.

Method	S1	S2	S3	S4	S5	Average of five participants
kNN	82.46%	76.15%	73.35%	79.88%	76.98%	77.76%
ANFIS	85.41%	81.51%	79.84%	82.67%	78.33%	81.55%
SVM	96.70%	89.70%	88.60%	93.50%	90.10%	91.72%

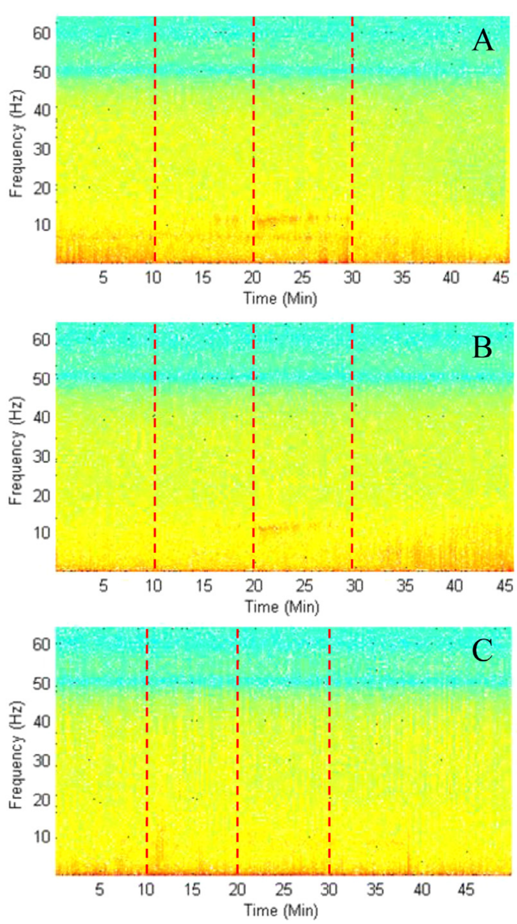

Fig. 7. Examples of EEG signal spectrograms from the EEG electrodes: Fz (A), Pz (B) for participant S1 and Fz (C) for participant S2.

using two other well-known classifiers in the literature and compared with the best results of the SVM-based classifier. In addition to SVM, kNN is a common method that a has been used for EEG classification recently (Hu, Li, Sun, & Ratcliffe, 2018; Ibrahim, Djemal, Alsuwailem, & Gannouni, 2017; Shah & Ghosh, 2018). According to the results given in Table 5, the kNN-based classifier yielded an average accuracy ranging from 73.35 to 83.46%, which was the worst result of all methods. Although not as widespread as kNN and SVM, Adaptive Neuro-Fuzzy System (ANFIS) is a method used in EEG classification problems (Bozkurt, Seçkin, & Coşkun, 2017; Deivasigamani, Senthilpari, & Yong, 2016; Madhusmita, Mousumi, Narayan, & Kumar, 2019). The ANFIS-based classifier in our study yielded a performance (78.33% to 85.41%) between kNN-based and SVM-based methods'. As the results indicate, the SVM-based method achieved the best performance on mental state detection.

Note that the common-subject mental state detector is clearly more useful than a subject-specific detection approach. However, we empirically observed that the common-subject detector could not classify the mental attention states in the EEG data very well. Accordingly, the necessity for subject-specific EEG decoders is much more mentioned in EEG BCI literature.

Finally, the contribution of each EEG channel in discriminating the different mental attention states is evaluated. For this task, the backward step-wise elimination procedure, which ranks the importance and the contribution of different EEG channels into the detection of the participants' mental states, was used. Specifically, the mental state detector with all EEG electrodes included was trained, and the drop of the average accuracy of the detector for all participants was quantified if an electrode was removed from the dataset. Then, the electrode with the smallest drop in the accuracy was permanently removed from the dataset. The procedure was then repeated until only one electrode remained. The results of this procedure (i.e. training/testing errors and average accuracy results vs. the number of EEG electrodes) are shown in Fig. 8. The order of the electrodes in the figure is F3-Fz-Cz-F4-Pz-C4-C3, left-to-right, thus identifying the ranks of the EEG electrodes in a decreasing order of importance. In Fig. 8, training and testing errors were calculated using MATLAB's *loss* function.

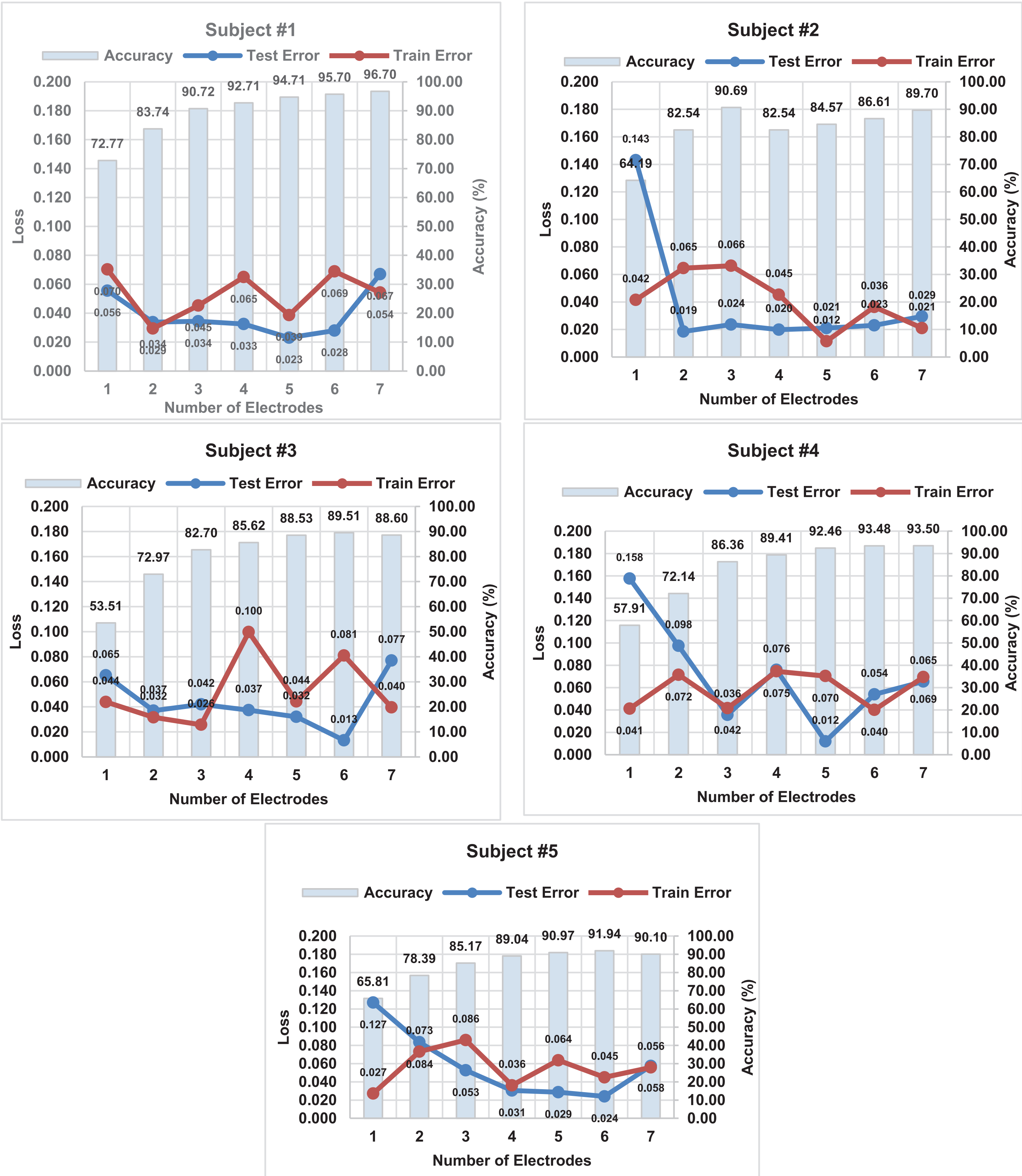

Fig. 8. Training/testing errors and average accuracy results using SVM vs. the number of EEG electrodes used in the EEG dataset for the subject-specific paradigm.

4. Discussion

In this study, the problem of detecting mental states in human subjects using EEG data was investigated. The problem of discriminating drowsing from attentive states using EEG data has been studied in the past in the context of car driving. Different from such studies, the present study performed the discrimination of the mental states engaged in passive observation or supervision tasks. The absence of active involvement in the task introduced substantial differences in this setting. Furthermore, three distinct mental states – focused, drowsing, and unfocused or detached, the latter being the state where subjects do not explicitly doze but lose the ability to respond to events due to the loss of focus nonetheless, were discriminated. The latter state has not been studied in the literature, although it presents a significant risk for process control and is significantly more interesting and difficult to detect, because such a "detached" mental state may not be manifested in any clear form via secondary, visually or otherwise observable cues or indicators. In that sense, we call the latter distinguished state a "pure" mental state. The methodology developed in the paper towards distinguishing this "pure" mental state can be applied more generally to discriminate subject states in different tasks and circumstances, as well as for the discrimination of different sets of states.

Many past similar studies focused on drowsiness of car drivers and, in another part, the assessment of stress in individuals engaged in mental workload tasks. Along with EEG monitoring, other methods such as video and movement monitoring were employed in that context. Although having been successful in previous studies, many such methods do not allow ready translation in different circumstances. The contexts in which individuals remain idle or passive present a special challenge for video- and movement-based alertness monitoring. EEG-based passive BCI offers a natural approach to address this problem by providing an easily transferrable methodology to monitor the mental conditions of the subjects. EEG signals connect directly with the neural activity of the brain and offer the opportunity to directly monitor the neural signatures of different mental states, avoiding the pitfalls of other state monitoring systems, such as those based on physical, visual, or physiological cues.

To study the problem of mental state detection and monitoring in this study, an original EEG dataset characterizing the engagements of the participants during a passive observation task was collected. An SVM-based method was proposed for detecting the changes in attention mental states. The SVM detector was trained on the samples of EEG data collected for subjects while being in target mental states. An ensemble of machine learning SVM classifiers were then used to implement the detection via an XOR-aggregation of multiple state-specific classifier outputs. The developed detector was shown to discriminate the mental attention states of focused, unfocused and drowsing with high accuracy using EEG signals only.

Table 6 summarizes the results of the previous studies on detecting mental attention states chronologically. As seen in Table 6, our study had better results than most previous studies. Analyzing the studies that gave close results, it is seen that they either used extra data that support the EEG signal or simply classified the attention using two states.

We found that it is important for the mental state detectors to be trained individually for subjects. We observed that a "generic" mental state detector could perform significantly worse than the subject-specific detectors, losing as much as 20–30% in detection accuracy over the 3 mental states mentioned above.

We examined which features in the EEG signals contributed to the identification of the mental states above. We found that the differences between focused and unfocused states were most clearly manifested in the low-frequency EEG activity, between 1 and 10 Hz. Namely the focused or engaged state was associated with elevated EEG power in 1–10 Hz band and disengaged or unfocused state was associated with the emptying of the EEG spectrum on this frequency band, as well as on other frequency bands. These changes were most clearly manifested over the frontal lobe. The relationship between delta-band EEG activity and the concentration of individuals has been reported in EEG literature in the past. However, we found it interesting that no significant signs of changes were seen in higher frequency EEG activity, such as beta or theta, which EEG literature associates with mental workload tasks. Drowsing state manifested itself via intermittent or continuous alpha-band power spikes at 10–15 Hz, consistent with the findings in the literature regarding the relationship between alpha EEG waves and drowsing.

We ranked the relative importance of different EEG electrodes in discriminating focused, unfocused, and drowsing mental states. We found that over 90% of the performance could be recovered with only 4 EEG electrodes, namely F3, F4, Fz, and Cz. Three of these electrodes were located over the frontal lobe. Neural activity in the frontal lobe has conventionally been associated with the individual's concentration. Thus, the frontal electrodes effectively distinguished between the subjects who were mentally engaged versus those not engaged. The parietal lobe is known to be associated with the development of alpha waves. Therefore, Cz electrode can be expected to facilitate the detection of the onset of drowsiness. In addition, in this study, SVM was used to classify the "unfocused" section and efficiency of electrodes areas.

The parameters of EEG signals relevant to the discrimination of different mental states are important for EEG signal acquisition subsystems of such mental state monitoring systems. Factors such as signal's bandwidth, resolution, and electrodes all affect the design and the cost of such systems. Our analysis indicates that a successful determination of the three mental attention states can be performed by using the EEG signals restricted to a frequency

Table 6
Comparison of previous studies in predicting the human's attention state.

Reference	Dataset	Method	Mental states predicted	Accuracy (%)
Li et al. (2011)	EEG	KNN	3 different attention levels	57.00
Liu et al. (2013)	EEG	SVM	2 states (i.e. attentive or inattentive)	76.82
Lee et al. (2014)	EEG and respiration data	SVM	6 levels (i.e. awake, slightly drowsy, moderately drowsy, extreme drowsy, sleep, deep sleep)	98.60
Ke et al. (2014)	EEG	SVM	3 levels (i.e. attention, no attention and rest)	76.19 −85.24
Wang et al. (2015)	EEG	SVM	2 states (i.e. driving or math task)	84.6 ± 5.8–86.2 ± 5.4
Djamal et al. (2016)	EEG	SVM	2 states (i.e. attentive or inattentive)	77.00–83.00
Myrden and Chau (2017)	EEG	SVM	3 states (i.e. fatigue, frustration, attention)	71.6–84.8
Alirezaei and Sardouie (2017)	EEG	SVM	2 states (i.e. attentive or inattentive)	92.80
Nuamah and Seong (2018)	EEG engagement index	SVM	2 states (i.e. attentive or inattentive)	93.33 ± 8.16
Acı et al. (2019)	**only EEG**	**SVM**	**3 levels (i.e. focused, unfocused, drowsy)**	**96.70 (best) 91.72 (avg.)**

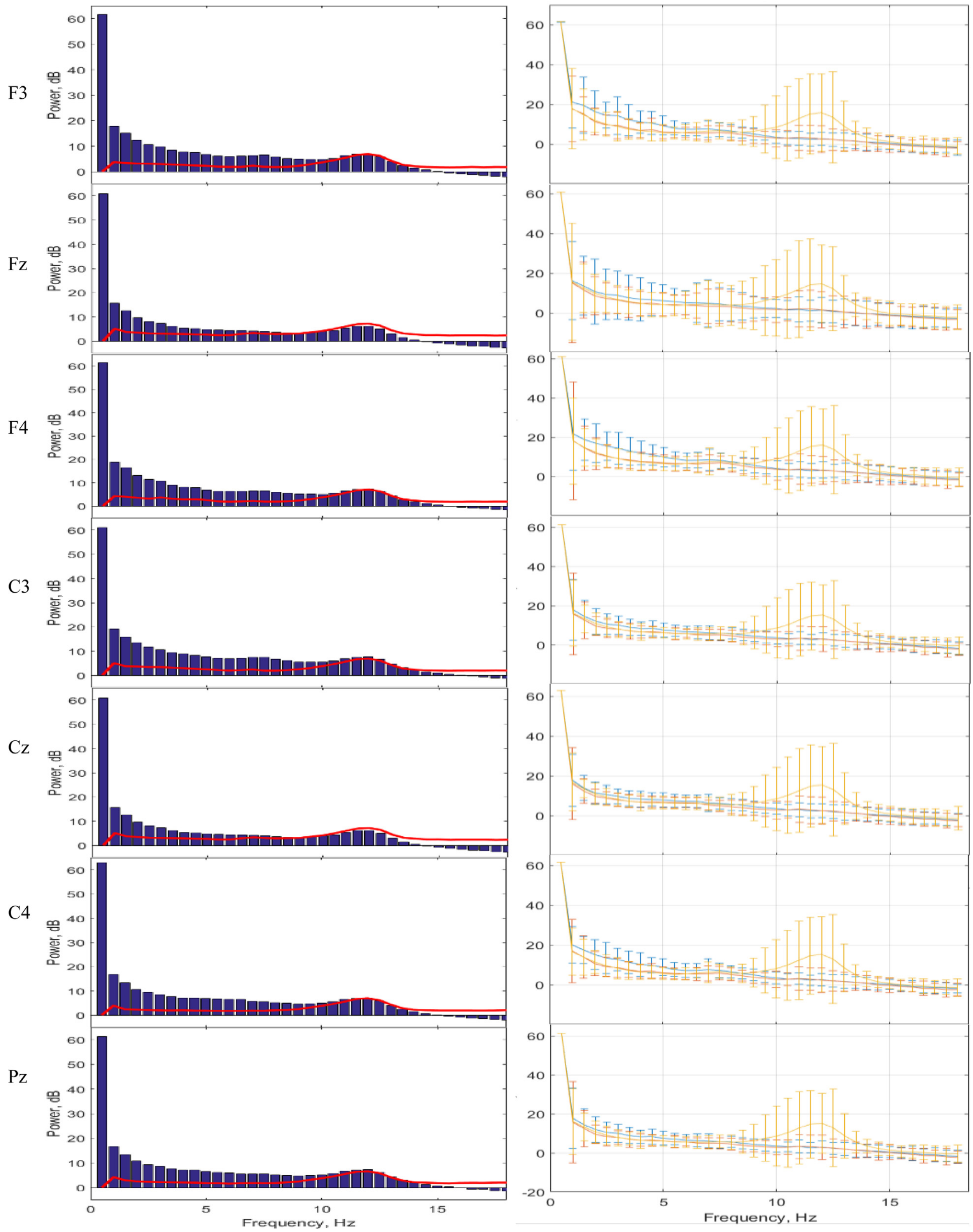

Fig. 9. Examples of the feature and their basic statistical properties for participant S1.

band below 20 Hz and using only 4 or 5 electrodes at F3, F4, Fz, Cz and possibly Pz locations. This indicates that the design of passive EEG BCIs for monitoring mental attention states can be done with hardware providing signal acquisition at the relatively low frequencies of 40–50 Hz and only 4 electrodes in the configuration above.

A big complication for practical applications of EEG-based technologies is the susceptibility of EEG BCI to motion artifacts and external electromagnetic interferences. EEG headsets are notorious for being easily affected and the signal for being distorted by subject movements or working nearby electrics and electronic devices. These factors are much less impactful in the context of this study, where the property of the individuals to remain motionless and in controlled indoor environments alleviated many of such problems.

At the same time, one of the key advantages of the methodology used here is its reliance on the identification of target states directly on the neural activity. Direct use of neural signatures learned while subjects implemented the desired target states makes such approach difficult to circumvent, confuse, or mislead, which is a significant risk when secondary signatures such as video or movement monitoring are used for mental state estimation. Moreover, our approach allows the detection of mental states that are not necessarily manifested clearly via physiological or visual signatures, or "pure" mental states as we term them. Finally, the methodology here can easily be generalized and applied to the detection of different mental states in a variety of different applications with minimal modifications.

More specifically, the method for detecting mental states in this work was investigated in the context of a specific continuous attention task. At the same time, the approach used is very general and can be applied to the problem of the detection of different mental states in different circumstances as long as individuals remain predominantly passive. Such applications may include, for example, the observation of in-patients and/or paralyzed and immobile patients in hospitals, etc. The key elements of the proposed methodology are: (i) obtaining samples of the EEG data associated with the mental states of interest using controlled simulation of such states, (ii) using machine learning to construct detectors for such states based on EEG data and in subject-specific and mental state-specific manners; (iii) combining the outputs of multiple machine learning detectors within a passive EEG BCI via XOR or similar aggregation technique. The analysis of the parameters of such constructed machine learning detectors can offer insights about the representation of different mental states in EEG signals.

The definition of the different mental attention states in the context of this methodology is done by means of self-reporting. The practice of self-reporting is widely accepted in psychological practice. In this study, the states of interest were defined as "focused: remaining concentrated, focused and actively paying attention to a task", "unfocused: remaining awake but not paying attention or reacting to a task", and "drowsing: dozing off with eyes closed or open". As such, the participants were instructed to implement those target states while the EEG data was collected. The subjects implemented such states over indicated intervals of time as they understood them.

In general, objective measures that can be used independently to identify the target mental states should be used whenever they exist. In our case, two factors precluded an introduction of such objective controls. First, given that one of the states to be identified in this study was disengagement, we found that any active probing of the state of the subjects resulted in the destruction of that state and the nullification of the experiment. Second, we could identify no clear visual metrics or signatures that could be

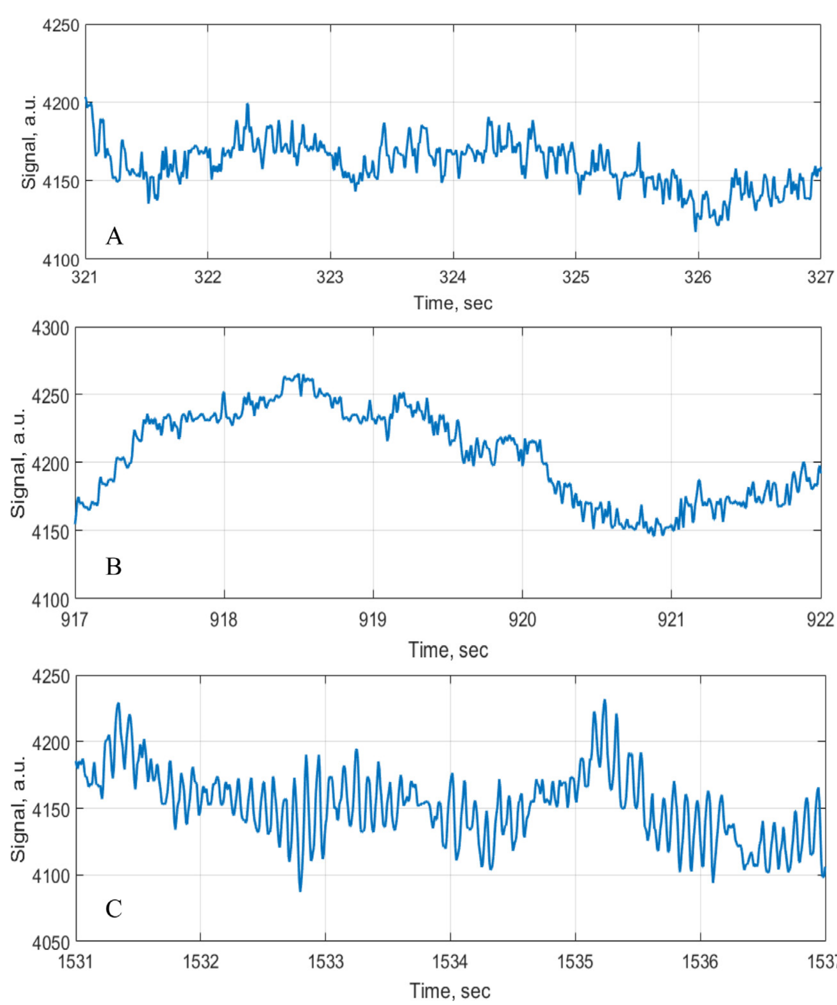

Fig. 10. Examples of the EEG recordings associated with different detected mental states for participant S1 and electrode Pz: (A) 'focused' (B) 'unfocused' (C) 'drowsy'.

associated with participants staying passively focused or really becoming disengaged. Therefore, the practice of self-reporting of the subjects was used as the primary means of defining the mental states in the context of this study.

On the other hand, the inspection of the EEG signals is shown in Figs. 9 and 10. In Fig. 9, left column: the mean (bar-plots) and the standard deviations (red line) of different features shown with respect to their corresponding EEG channel and frequency. Right column: mean and standard deviations of different features within different mental state periods. Blue is the 'focused' state, orange is the 'unfocused' state, and yellow is the 'drowsy' state. Error-bars show the within-group standard deviations of each feature.

Figs. 9 and 10 reveal that there are clear, objective, and quantifiable differences in the shape and characteristics of the EEG signals observed over the 3 periods of time where the subjects were instructed to implement the 3 different attention states. The objective differences were mapped to the periods of time when the subjects self-identified themselves as being focused / concentrated, disengaged / unfocused, and drowsing, respectively.

5. Conclusions

In this study, we developed a passive EEG BCI for monitoring a set of mental states of human individuals. We collected a new EEG dataset related to individuals engaging in a passive supervision task. We demonstrated with high accuracy the detection of 3 mental attention states, namely passive attention, disengagement, and drowsiness of passive individuals in a task. The accuracy of the discrimination of engaged or focused, disengaged or unfocused, and drowsing states reported in this work reached 96.70% (best) and 91.72% (avg.) and can be of use for driver security applications. The SVM-based EEG BCI approach used in this study allows a ready-to-use machine learning model, generalized for other scenarios, including the detection of different mental states and a variety of different circumstances. The analysis of the parameters of constructed mental state detectors can provide new insights into the representation of such states in the EEG signals.

One of the particularly interesting areas of the generalization of this study is related to clinical applications that require assessment or monitoring of the mental states of subjects. One, although not necessarily the only example of such an application, is the bispectral index monitoring (BIS), one of the technologies for monitoring the depth of anesthesia. BIS is a known, albeit proprietary, technology that relies on monitoring the electroencephalographic brain signals to produce a depth of anesthesia index that helps anesthesiologists reduce the incidence of intraoperative awareness of patients. Although the algorithms behind BIS are proprietary and have not been disclosed, BIS is an empirically derived measure computed as a weighted sum of several electroencephalographic parameters calculated in the time domain, frequency domain, and high order spectral representations (Chalela et al., 2018). A single value ranging from 0 (equivalent to EEG silence) to 100 is thus derived to indicate the level of general an anesthesia, based on the electroencephalographic activity of the brain. The construction of bispectral index is similar to the approach used in this study and can be extended for novel clinical applications in the future.

Declaration of Competing Interest

None.

Credit authorship contribution statement

Çiğdem İnan Acı: Supervision, Formal analysis, Conceptualization, Writing - original draft, Writing - review & editing. **Murat Kaya:** Data curation, Software, Funding acquisition, Writing - original draft. **Yuriy Mishchenko:** Supervision, Conceptualization, Writing - original draft.

Acknowledgments

All experiments in this work were performed with healthy volunteer participants chosen among the students of the Faculty of Engineering at Toros University (Mersin, Turkey). All participants signed the informed consent form after receiving the instructions about the experiments' objectives and procedures, in accordance with the ethical guidelines of Mersin University. This study is supported by Mersin University Department of Scientific Research Projects (Project Code: 2018-3-TP2-3064). This academic work was linguistically supported by the Mersin Technology Transfer Office Academic Writing Centre of Mersin University.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.eswa.2019.05.057.

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