Monitoring Human Attention with a Portable EEG Sensor and Supervised Machine Learning

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Abstract

For several healthcare applications, it is important to monitor the attention level of people, especially in the fields of rehabilitation and psychology. The recent availability of cheap and portable EEG readers has enabled continuous and unobtrusive acquisition of EEG signals. Those signals may be preprocessed and analysed with machine learning algorithms to estimate the attention level of people without interfering with their current activities. In this paper, we report our experience with attention level estimation using two kinds of devices: an off-the-shelf portable EEG headset, and a more sophisticated EEG device.

Keywords

Pervasive healthcare, human attention monitoring, EEG sensor data, supervised machine learning

1. Introduction

The increasing availability of portable and wearable sensors, more and more integrated in everyday objects, is paving the way to a new generation of applications to support personal health and well-being. Consequently, impressive research efforts have been devoted to devise effective techniques for recognizing human activities and complex behaviors based on those sensor data [1, 2, 3].

Interestingly, while a vast amount of healthcare applications use sensor-based artificial intelligence for addressing the physical dimension of health, the mental dimension is less investigated [4, 5]. However, a substantial portion of the world's population deals with mental disability. Many people with mental illnesses do not have equal access to healthcare, education, and employment opportunities, do not receive specific disability-related services, and experience exclusion from everyday life activities. Unfortunately, there is a large amount of diverse mental disabilities, which require ad-hoc and personalized solutions. Moreover, the design and implementation of effective and efficient technologies is a complex and expensive process involving challenging issues, including usability and acceptability.

In this paper, we evaluate the use of a cheap and unobtrusive portable electroencephalography (EEG) sensor for monitoring the human attention level. Indeed, the ability to monitor human attention is fundamental for treating several conditions, including the diagnosis and rehabilitation of children with attention-deficit/hyperactivity disorder [6]. We propose a feature extraction technique based on sliding windows, and supervised machine learning to distinguish between attentive and distracted states. We experimentally compared the performance of the portable EEG sensor with a more powerful EEG device using real-world datasets. Results indicate that the accuracy achieved by the simpler EEG sensor is close to the one achieved by the more sophisticated device. Moreover, the technique provides reliable results when the machine learning algorithm is trained on the specific subject, while accuracy significantly drops when the algorithm is trained on other subjects. This study provides useful indications and outlines different research directions for improving the approach in future work.

2. Material and methods

In our work, we have considered two datasets containing brainwave data on which we have applied the same feature extraction and classification techniques. The first dataset, named 'Image-labeling dataset', was acquired using an off-the-shelf portable EEG headset with 4 channels. The second dataset, named 'Epoc', was acquired using a more sophisticated EEG device with data acquired from 7 channels. We experimented the performance of machine learning algorithms in distinguishing attentive, distracted, and drowsed states of the individual based on EEG signal processing. In our experiments, only the preprocessing phase of EEG data diverges. Indeed, the data of the Epoc dataset are raw, so it was necessary to employ Fast Fourier transform algorithms to extract Delta, Theta, Alpha and Beta brainwaves. Delta waves are related to deep sleep, unconsciousness, anesthesia, and lack of oxygen; Theta waves activity occurs when a person experiences emotional pressure, unconsciousness,

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or deep physical relaxation; Alpha waves are instead visible when an individual is in a state of consciousness, stillness, or rest, whereas when one is thinking, blinking or otherwise stimulated, this wave type disappears (alpha block); finally, Beta waves is evident when a person thinks or receives sensory stimulation.

2.1. Image-labeling dataset

The first dataset, collected by our research group, considers the attention level of annotators labeling a series of images. A detailed description of the dataset can be found in [7]. For the EEG data collection, we used the Muse2 headband version 2 of InteraXon[1]. Muse consists of 4 electrodes that can collect information on brain activity with a 256Hz sampling frequency in a non-invasive way. The Muse electrodes gather signals from channels TP9, AF7, AF8 and TP10. These electrodes are named and positioned according to the International System 10-20 [8]. We used the mobile application Mind Monitor[2] along with the Muse sensor for receiving the EEG signals. For the sake of this work, we collected:

- The date and time of the recording.
- Brainwaves Delta, Theta, Alpha, Beta [9] for each sensor.

The brainwave values are absolute band powers, based on the logarithm of the spectral power density (PSD) of the EEG data for each channel. These values are calculated internally by the Mind Monitor application with a data rate of 10Hz.

The participant's task was to label indoor images that appeared randomly in a data annotation interface by selecting one of the eight buttons with the correct label. The task took 30 minutes to complete. At the end of the task, the 'Attentive' and 'Distracted' classes were assigned to the first 10 and last 10 minutes of the recording, respectively.

2.2. Epoc dataset

The second dataset was taken from the work of [10]. For the EEG data collection, the authors used the Epoc EEG headset [3] with 12 electrodes. The data are collected with a sampling rate of 128 Hz. The device was modified to allow electrode placement on the frontal and parietal areas of the scalp. Among the available channels, only O1, O2, P7, P8, AF4, F3, F7, named and positioned according to the International System 10-20, were used in the presented work, since the other ones gave no insightful information for attention monitoring, or were affected by an excessive level of noise.

Since brainwaves data in the dataset are raw, we preprocessed the data by applying the fast Fourier transform [11] to obtain Delta (0.5-4 Hz), Theta (4-8 Hz), Alpha (8-14 Hz) and Beta (14-30 Hz) brainwaves. The participant's task consisted of controlling a train using the Microsoft Train simulator program, through simple keyboard commands, for a minimum duration of 30 minutes. At the end of the task, the recording is divided into three 10-minute fragments related to a particular mental state: 'Attentive' during the first fragment, 'Distracted' during the second one, and 'Drowsed' during the last one.

2.3. Feature extraction

The various brainwaves signals were divided into 10-second long non-overlapping sliding windows. For each window, we calculated 7 features: mean and median, variance and standard deviation, maximum, minimum, and difference between maximum and minimum values.

These features are computed for each value of brainwaves Delta, Theta, Alpha, Beta, for each channel. Hence, we use 112 features for the Image-labeling dataset (4 channels), and 196 features for the Epoc dataset (7 channels).

2.4. Classification of human attention level

Feature vectors are used to train and test a Random Forest (RF) classifier [12]. In various problems and classification domains, including problems with small training datasets, RF have often been found among the most accurate classifiers. RF and random trees were also successfully used for run-time brain-computer interface applications [13]. The RF randomly selects a subset of the available features to train a decision tree classifier on it; then it repeats the process with other subsets of random features to generate many decision trees. The final decision is made by combining the results of all decision trees using an ensemble approach.

3. Experimental evaluation

Our technique has been evaluated using two cross validation approaches. In the first approach, named subject-specific cross validation, the data of each volunteer was taken into account separately, performing a sequential 5 fold cross validation on each volunteer's dataset. In the second approach, which we name leave-one-person-out cross validation, k fold cross validation was carried out, in which each fold corresponds to the data collected by a single volunteer.

The results obtained by applying the first cross validation approach to the Image-labeling dataset are reported

[1] https://choosemuse.com/
[2] https://mind-monitor.com/
[3] https://www.emotiv.com/epoc/

in Table 1 and the results obtained by applying the second cross validation approach to the same dataset are reported in Table 2. Table 1 shows very different results among the subjects, ranging from an Accuracy of 62% to 100%, probably due to the headband that is sensitive to movement and not easy to place in the correct position. The second approach obtained an average Accuracy of 61% (Table 2), probably due to inter-subject variability of acquired EEG data. Overall, the subject-specific approach achieves better results (80% average Accuracy) than the leave-one-person-out approach.

Dataset	Accuracy	Confusion Matrix		
Tester 1	68%	Attent.	Distract.	
		41	19	Attent.
		19	41	Distracted
Tester 2	62%	Attent.	Distract.	
		47	13	Attent.
		32	28	Distracted
Tester 3	86%	Attent.	Distract.	
		49	11	Attent.
		5	55	Distracted
Tester 4	84%	Attent.	Distract.	
		50	10	Attent.
		9	51	Distracted
Tester 5	82%	Attent.	Distract.	
		48	12	Attent.
		10	50	Distracted
Tester 6	100%	Attent.	Distract.	
		60	0	Attent.
		0	60	Distracted
Overall	80%	Attent.	Distract.	
		295	65	Attent.
		75	285	Distracted

Table 1
Image-labeling dataset. Subject-specific cross validation.

Accuracy	Confusion Matrix		
61%	Attent.	Distract.	
	207	153	Attent.
	130	230	Distracted

Table 2
Image-labeling dataset. Leave-one-person-out cross validation

Table 3 and Table 4 report the results of the subject-specific approach applied to the Epoc dataset to solve the attentive/distracted and attentive/drowsed classification problems, respectively. Finally, Table 5 and Table 6 show the results obtained by applying the leave-one-person-out approach to the Epoc dataset to solve the same problems. We can make similar considerations to those made previously comparing the results of Tables 1 and Table 2, although in this case, the gap between the results obtained with the application of the two approaches is less evident. In particular, in the subject-specific approach, we have an overall Accuracy of 72% (Table 3) and 86% (Table 4), compared to an accuracy of 68% (Table 5) and 80% (Table 6) obtained using leave-one-person-out cross validation.

Dataset	Accuracy	Confusion Matrix		
Tester 1	57%	Attent.	Distract.	
		175	125	Attent.
		131	169	Distracted
Tester 2	71%	Attent.	Distract.	
		234	66	Attent.
		107	193	Distracted
Tester 3	77%	Attent.	Distract.	
		229	71	Attent.
		59	231	Distracted
Tester 4	78%	Attent.	Distract.	
		196	44	Attent.
		62	178	Distracted
Tester 5	76%	Attent.	Distract.	
		174	66	Attent.
		50	190	Distracted
Overall	72%	Attent.	Distract.	
		1008	372	Attent.
		409	961	Distracted

Table 3
Epoc dataset. Subject-specific cross validation. Attentive/distracted classification.

Dataset	Accuracy	Confusion Matrix		
Tester 1	75%	Attent.	Drowsed	
		204	96	Attent.
		52	248	Drowsed
Tester 2	87%	Attent.	Drowsed	
		281	19	Attent.
		58	242	Drowsed
Tester 3	89%	Attent.	Drowsed	
		289	11	Attent.
		53	247	Drowsed
Tester 4	92%	Attent.	Drowsed	
		223	17	Attent.
		20	220	Drowsed
Tester 5	89%	Attent.	Drowsed	
		210	30	Attent.
		21	219	Drowsed
Overall	86%	Attent.	Drowsed	
		1207	173	Attent.
		204	1176	Drowsed

Table 4
Epoc dataset. Subject-specific cross validation. Attentive/Drowsed classification.

Accuracy	Confusion Matrix		
68%	Attent.	Distract.	
	940	440	Attentive
	429	951	Distracted

Table 5
Epoc dataset. Leave-one-person-out cross validation. Attentive/distracted classification.

Accuracy	Confusion Matrix		
80%	Attentive	Drowsed	
	1094	286	Attentive
	240	1140	Drowsed

Table 6
Epoc dataset. Leave-one-person-out cross validation. Attentive/drowsed classification.

4. Discussion and research directions

Considering the Image-labeling dataset, we can observe that the average accuracy of distinguishing attentive and distracted states is 80% when we use a subject-specific cross validation approach; i.e., when the classifier is trained on the data of the same individual used for testing. Unfortunately, when we use a leave-one-person-out cross validation approach, the accuracy drops to 61%, which is a rather weak result for a binary classification problem. With the latter approach, we use more extensive training data, but those data are acquired from different people than the individual used for testing.

With the Epoc dataset, we achieved similar results. Indeed, the average accuracy of distinguishing attentive and distracted states is 72% when we use a subject-specific cross validation approach. With the same approach, the average accuracy of distinguishing attentive and drowsed states is 86%. The recognition achieved with the latter problem is higher, probably because drowsiness is easier to distinguish from attentiveness with respect to distraction. Also with this dataset, using a leave-one-person-out cross validation approach determines a considerable drop of accuracy; i.e., 68% accuracy in distinguishing attentive from distracted states, and 80% accuracy in distinguishing attentive from drowsed states.

These results indicate that our method achieves relatively high accuracy only when the system is trained with data acquired from the final user of the system. Training the system with data acquired from different persons determines a relevant drop in accuracy. This fact undermines the practical utility of this technique for some applications, since the system would require an initial training phase by the user which may be time-expensive and uncomfortable. This problem may be addressed by using transfer learning methods explicitly proposed for EEG data [14].

Another worth noting finding of our experiment is that the more sophisticated device used for the Epoc dataset achieves essentially the same accuracy of the simpler device used for the Image-labeling dataset. This result indicates that even an off-the-shelf device may be effective to support some attention-aware applications. Future work includes investigating different machine learning algorithms for the classification task, including deep learning methods, to improve the accuracy of the system, and feature selection techniques to reduce overfitting.

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