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Attention level monitoring based on EEG measurement

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Abstract. This paper reports on research into the daily use of EEG measurement, based on brain-computer interface (BCI). Its purpose is to present a series of visualized data, clearly showing the attention level of the user's brainwave This method of recognizing the attention level can be used in a variety of practical ways, such as assessing students' cognitive functions, detecting drivers' fatigue levels, and clinical application in supervising the moods of patients, especially those with mental diseases. By attaining different dimensions of brain waves, which are sorted into alpha waves, beta waves and meditation, helping to evaluate attention levels, this device can deal with the raw data via inner codes and output relatively accurate results.

Keywords: EEG, Attention Level, brain waves.

1. Introduction

In today's fast-paced society, people often find themselves struggling to maintain focus and stay calm during their daily activities. Attention is tremendously important in many aspects. Focus is very important for work because it helps people complete tasks effectively. At work, focus can also help us plan and organize our work better, increasing productivity and results. Concentration is also very important for learning because it helps students to remember and understand what they are learning better and improve their academic performance. At the same time, concentration can also help students better manage time, assign tasks and optimize learning methods. the impact of working memory and attention is largely channeled through word reading and listening comprehension. Working memory directly influenced word reading and listening comprehension, both of which played a significant role in explaining the variability in reading comprehension. Additionally, attention influenced reading comprehension, which was partially explained by its impact on listening comprehension.[1]

electroencephalography (EEG) is defined as the electrical activity of an alternating type recorded from the scalp surface after being picked up by metal electrodes and conductive media.[2] Its advantage over other techniques is that it's completely not invasive, which means it could probably fit most people, including children and the old. Furthermore, as it's based on electrical interaction between the equipment and the user, there are few risks and it's possible to use it repeatedly and in the long term.

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Modern technologies are applied to measure the states of human bodies. For instance, there are electrocardiography (ECG, heart), electromyography (EMG, muscular contractions), electrogastrography (EGG, stomach) etc. Within those measurements, EEG, detecting fluctuations and changes in brain waves, can most clearly present users' attention levels. Also, there have been different techniques of measurements put into use, such as computer tomography (CT), magnetic resonance imaging (MRI) and positron emission tomography (PET). By taking convenience and practicality into consideration, finally, we chose a simplified device that contains only one electrode, in contact with the user's forehead, to detect the brain waves produced during brain activities. This is an effortless way to detect and it is also cheap compared to equipment with 64-electrode

2. Methods

To guarantee the reliability of the final results, the device is designed to detect data from 3 different aspects of a human's brain waves: alpha wave, beta wave, as well as meditation. (Alpha and Beta waves are further divided into high part and low part) Alpha waves are characterized by their prominent amplitudes and are detected during periods of moderate brain activity. They specifically appear when an individual is momentarily at rest but still alert. Increased alpha wave activity is connected to an elevated sense of calmness. Beta waves are generated during periods of increased alertness and can be identified through EEG measurements. There exists a connection between beta waves and enhancements in cognitive capabilities.[3]

Table 1. We use five channels for data filtering

	A	B	C	D	E	F
1	High Alpha	Low Alpha	High Beta	Low Beta	Mediator	label
2	588	510	1848	1090	43.2	1
3	322	250	1028	732	38.4	1
4	394	370	1100	768	72	1
5	354	308	1108	740	44	1
6	168	162	872	586	40	1
7	250	180	838	632	54.6	1
8	228	202	862	626	61.6	1
9	282	120	854	592	70.2	1
10	238	230	872	616	71	1

Considering individual distinction, one device is designed for one specific user. We chose a volunteer for data collecting. We collected enough filtered data separately while he was in different moods and states. After a series of feature extraction and training in Multilayer Perceptron (MLP) neural network, we got a relatively stable standard for attention level ranking of him. As a result, this volunteer could use this database for his future use of testing his attention level of himself.

Figure 1. This is a photo of a volunteer wearing the device

We made efforts to filter noises made from influence factors by means of the Fourier Transform. Then we started the process of collecting useful data. In order to gain a universal standard to evaluate attention levels, we sampled data from one volunteer, who was tested separately when he was in different moods. After processing the data recorded from EEG by feature extraction, we put the data into Multilayer Perceptron (MLP) for deep learning. Deep learning functions by comprehending complex relationships within features through a layered approach. The core requisites include high-speed computers and substantial data for training large neural networks.[4] MLP, which is a type of Artificial Neural Network, ANN, can learn abstract representations of data. It can analyze the data provided to it, which includes five columns of arrays representing a duration of one and a half hours, encompassing both relaxed and tense states. These columns are labelled as "Low Alpha wave," "High Alpha wave," "Low beta wave," "High beta wave," and "Meditation." Through exposure to this data, the model can learn and discern patterns. The data is organized into six groups, with each group covering half an hour. The relaxed states are labelled as 1, while the tense states are labelled as 0. This labelled dataset is utilized for training the system.

3. Results

Eventually, the system becomes proficient at determining whether the signal at a given moment signifies relaxation or tension based on the array of values from the five columns within a 30-minute interval. The attained accuracy of our approach is approximately 70%. This accuracy rate is considered meaningful in our context, as it demonstrates that the information obtained from a single electrode is substantial. Adding another electrode might significantly enhance the accuracy even further.

As a result, we consider that Increasing network depth can lead to an error rebound. This is attributed to factors like model capacity and training epochs. To avoid excessive training, an early stopping technique is employed, aiming to identify the ideal number of iterations. This technique involves dividing the dataset into training, validation, and test sets. During training iterations, the process halts if the validation set ceases to decrease for a specific number of epochs.[5]

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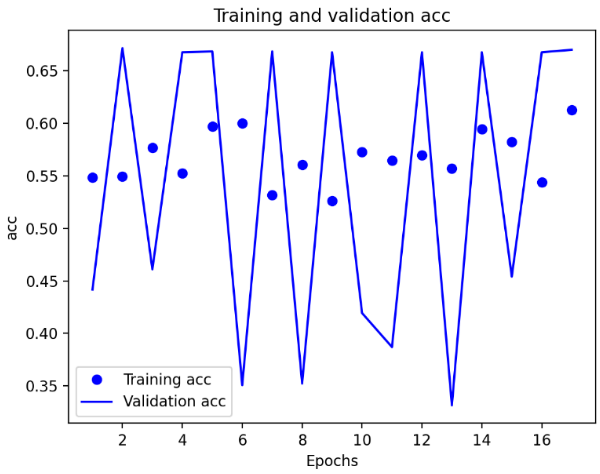

Figure 2. We can observe that the training accuracy remains consistently high, while the validation accuracy remains consistently low. From this, we can deduce that the model's generalization ability is not very strong, indicating an issue of overfitting.

4. Discussion

However, the biggest challenge that we faced was that due to a decrease in the size and a simplification in the operation, we had no choice but to sacrifice some of its accuracy. The disadvantage appeared to be some noises shown on the screen because of influence factors from the environment. Apart from that, we had to solve the problem that some tiny actions such as blinking might have an influence on brain waves that may disturb the data processing and assessment. In order to guarantee our results' reliability, we should obtain more data for the neural network to learn, to achieve higher accuracy. Furthermore, our experiment is lacking universality, since we only collect data from one participant. We will find more participants in the future to generalize our device. We could also try to use more electrodes to increase accuracy. As advanced scalp EEG arrays with high electrode density (ranging from 64 to 256 electrodes) enable the localization of brain sources with a level of precision that can extend to sub-lobar regions.[6]

5. Conclusion

Overall, we aim for using this simple device to assess people's attention levels, so they can notice that they are not paying attention, to increase their study/work efficiency and reduce the risk of having accidents. We use a neural network to train a series of data of Alpha wave, Beta wave and meditation these three filters to find the attention level and we get an accuracy of about 0.72. our experiment is only for one participant, it should be tested for universality further.

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