

Comparison of Brainwave Sensors and Mental State Classifiers

Hironori Hiraishi, Ashikaga University, Japan*

 <https://orcid.org/0000-0002-0447-9114>

ABSTRACT

Brain-computer interfaces (BCIs) have been attracting attention as a research topic. BCI has various applications, such as at home and in the medical sector. BCI is an interconnection between the human brain and a computer, which is a communication pathway between external peripheral devices. Brainwave sensors play a significant role when applying BCIs in practice. In this study, data from such sensors are analyzed to classify the mental states of users. This study used two different brainwave sensors: Neurosky MindWave Mobile and Emotiv EPOC+. Several types of machine-learning techniques (support vector machine, random forest, and long short-term memory) have been applied to classify brainwave data. This study aimed to compare the accuracy of the two sensors, analyze data, and identify the most accurate machine-learning method. Finally, a BCI toy with MaBeee, which is a battery-type internet-of-things device, was designed as a BCI application that reflected the analysis results.

KEYWORDS

BCI, BCI Toy, EEG, IoT, LSTM, Machine Learning, Random Forest, SVM

1. INTRODUCTION

Brain-computer interfaces (BCIs), which can be applied in various areas, such as home use, robotics, and medical settings, have been widely investigated. BCIs represent an interconnection between the human brain and the computer and serves as a communication pathway between external peripheral devices. Previously, BCI was a complex term for non-researchers; furthermore, previously, specific equipment and environments required to measure the different states of the brain were not easily accessible. Over the past decade, portable and simplified electroencephalogram (EEG) sensors have been developed. An EEG is used to evaluate the electrical activity of the brain and is one of the most popular non-invasive techniques for recording brain activity. Currently, many EEG sensors are available, thus allowing BCIs to be investigated extensively. Examples include the operation of computers (Márquez et al., 2018) and web browsing applications (Halder et al., 2015), control of wheeled robots (Alsammarraie & Inan, 2022; Hiraishi, 2015) and robot arms (Ranky & Adamovich, 2010), cognitive state analysis in sports (Hiraishi, 2021) and driving (Hiraishi, 2020), patient monitoring (Kumar et al., 2015), and some medical applications (Saravanarajan et al., 2021; Ting et al., 2021). Thus, many topics related to BCI in diverse areas have been reported.

Brainwave sensors play a significant role in BCI application, and the data from such sensors are analyzed to classify the mental states of users. Therefore, the authors used two different brainwave

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*Corresponding Author

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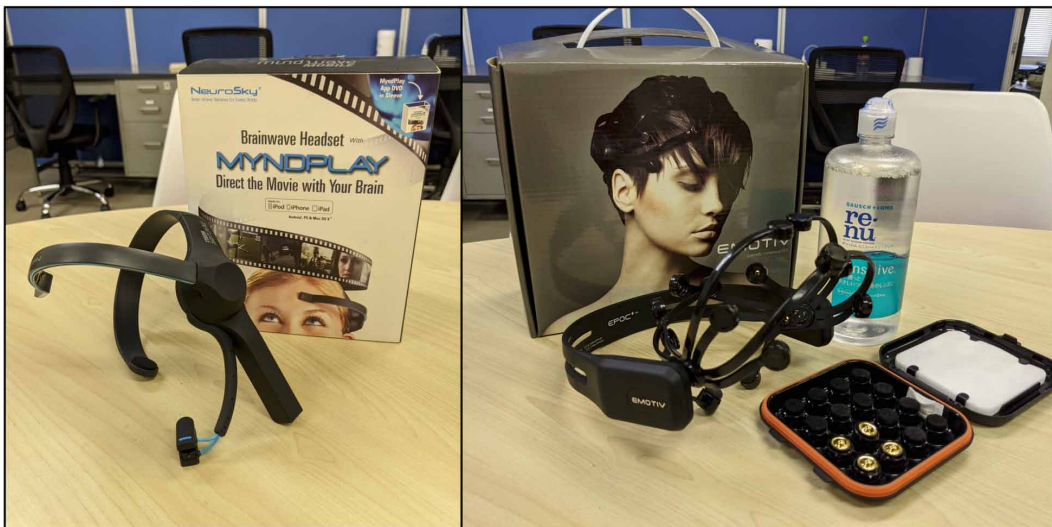
sensors: Neurosky MindWave Mobile and Emotiv EPOC+. These sensors have been widely used in many studies, such as the ones mentioned above. Several types of machine-learning techniques have been applied to classify brainwave data. This study aimed to compare the accuracy of the two sensors, analyze the data, and identify the most accurate machine-learning technique. The following machine-learning methods were the focus of this study: the support vector machine (SVM), random forest, and long short-term memory (LSTM). SVM and random forest are among the most popular and effective methods to be proposed before the advent of deep learning. LSTM is a deep learning method—a type of recurrent neural network—and is advantageous in that it allows the analysis of time-series data such as brainwaves. These methods are typically used for brain data analysis (Costantini et al., 2009; Edla et al., 2018; Liao et al., 2018; Roy et al., 2019; Ting et al., 2021). That is the reason why they were selected in this study.

This study focused on three classes of mental states: “attention,” “meditation,” and “other.” The brainwave data for each class were obtained using each sensor from three subjects and then analyzed using each method. Subsequently, the characteristics of the brainwave sensors and mental state classifiers were clarified by comparing the accuracy of each combination. Finally, a BCI toy with a battery-type Internet-of-Things (IoT) device was designed as a BCI application to demonstrate the analysis results.

2. BRAINWAVE SENSORS

Figure 1 shows the two brainwave sensors adopted in this study, namely MindWave Mobile from NeuroSky Inc. (on the left) and EPOC+ from Emotiv Inc. (on the right), both of which are EEG sensors.

Figure 1. MindWave Mobile (left) and EPOC+ (right)



EEG scans are performed by placing small metal disks—known as EEG electrodes—on the scalp. These electrodes identify and record electrical activity in the brain. The obtained EEG signals are amplified, digitized, and then sent to a computer or mobile device for storage and data processing.

MindWave Mobile is an extremely simple and user-friendly sensor with a single channel, which comprises only two electrodes at the forehead and ear. The headset’s sensor measures the brain’s electrical activity between the forehead and ear; it transfers the data via Bluetooth to a computer,

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