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Decoding EEG Signal for Consumer-grade EEG Device for Grasp and Lift Task

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1. Introduction

BCI Technologies have been developed in many kinds of research in recent years. While BCI technology is applied to various fields from controlling simple wheelchair movement to controlling complex robotic hands, most devices used are high-grade EEG devices with a large number of channels and sampling frequency rate, or invasive surgical methods. For this reason, the application of these products to become consumer products is difficult for reasons of price and complexity. In addition, EEG datasets are expensive to get considering the many factors such as artifacts and the long preparation and recording process. For that reason, this paper aims to use publicly available data with different specifications, and perform classification tasks using target EEG device specifications. In this case our target specification same as one of the commercial EEG devices with 14 channels and a 128 Hz sampling frequency.

2. Related Works

The results of analyzing EEG devices for task classification have been published in many studies. In the study, Ofner et al.[1] classified six different types of movements of the upper limbs. The research classified movement and rest execution tasks using 61 channels and 512 Hz sampling frequency with 87 percent accuracy. However, when comparing different movements, the result is lowered to 55 percent accuracy. On the other hand, Bressan et al.[2] with the help of 64 gel-based channel electroencephalograms, have decoded two different hand movement datasets influenced by Movement Related Cortical Potentials (MRCPs) by recording brain activity with 58 electrodes and 6 Electrocardiogram (EOG). With convolutional neural networks (CNN), the research obtained 70 percent average accuracy and 64 percent average accuracy on the datasets, respectively. While those researches show the potential and effectiveness of neural networks to process EEG data, this study focuses on how to implement decoding hand movement using a lower number of channels and sampling frequency.

3. Methodology

3.1 Data

The publicly available Grasp and Lift dataset [3] was analyzed for this research. Data were obtained from 12 participants who performed the grasp-and-lift task repeatedly for 30 trials for every subject. For each repetition, every subject grasped an object with the right thumb and index finger. The subjects lifted and held the object for a few seconds, then released and returned to the starting position. In this research, only EEG data and associated signal labels were used. There are 6 tasks for Grasp and Lift task dataset, HandStart (the hand starts to move), firstDigitTouch (first digit touched the object), bothStartLoadPhase (both digits have touched the object), LiftOff (the object lifted off from the support), Replace (object put back to support), BothReleased (both digits have released the object). Fig. 1 shows the signal in the time series for channel Fp1 while Fig. 2 show the corresponding task happened synchronously. Both of those figures represent the data recorded in one trial on one subject.

3.2 Pre-Processing

A variety of artifacts can affect EEG data, including movement, muscle activity, and interference from power lines. Due to this, it is difficult to use end to end method. Pre-processing the EEG data is crucial to obtaining an accurate result due to the high levels of noise and artifacts in the data. Various studies about EEG signals have demonstrated the ability to decode EEG information at low frequencies. In the study by Bressan et al.[2] shows signals are band-pass filtered between 0.01 Hz and 100 those figures the movement of the hands. This is due to the activity of EEG data being in the range of 0.5 Hz and 100 Hz, although the band may differ depending on the subject's age or gender. Then data is resampled to recreate data in the target EEG device and normalized. Normalization is to ensure that the model is not biased to the factor of each device has different voltage ranges and biases.

3.3 Classification Process

Machine learning algorithms for classification such as Neural networks are used for the classification of EEG data. In this study, the classification is focused on the true label in the data.

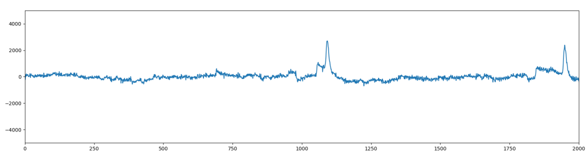

Fig. 1: Channel Fp1 Signal Figure

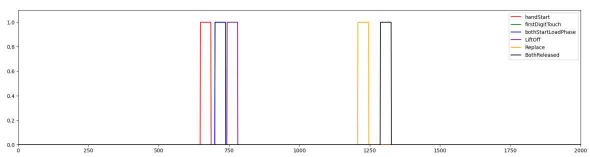

Fig. 2: Label Figure

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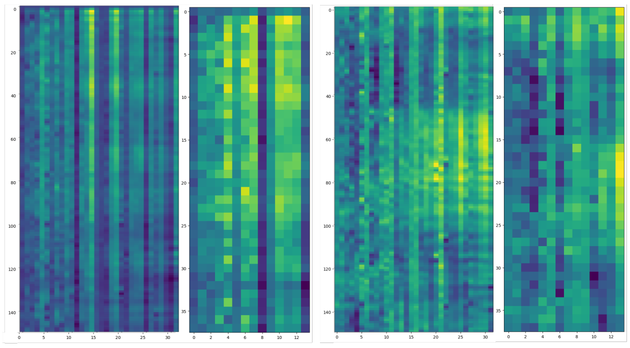


(a) handStart (b) Replace

Fig. 3: 32 channels(500Hz) and 14 channels(128Hz) True Label

3.4 Evaluation Method

To evaluate the performance of the classification, the result of task prediction is compared with the actual task from test label data. Then the accuracy of the model will be the number of correct prediction task over all prediction task.

4. Experiment and Result

4.1 Pre-Processed data

The original data was in 32 channels and 500 Hz sampling frequency. A Band-pass filter was applied to the data for 0.1 - 150 Hz then filtered to 14 channels and re-sampled to 128 Hz to match with target specification. Then the data is normalized with

$$x_i' = \frac{x_i - \mu_c}{\sigma_c} \quad (1)$$

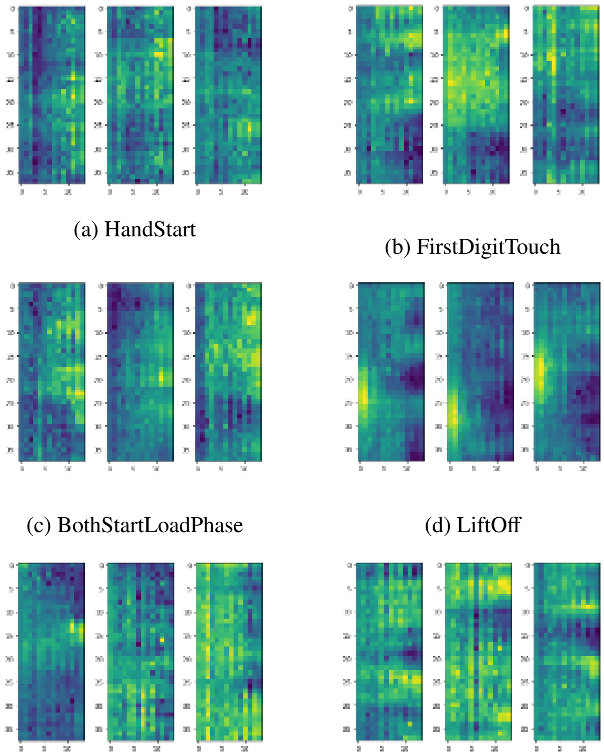
where x_i is the i-th data point, μ is the mean of the data in channel c, and σ_c is the standard deviation of the data in the c channel. The data is reshaped into (time window, channel) where original data is in (32,150) shape and after pre-processed data is in (14,38) shape. Fig. 3. shows the difference for 32 and 14 channels data for the same task.

4.2 Classification

In this study, image classification-based neural networks are used as the classification approach. The event-related signal data was captured, resulting in two-dimensional data (channels x time window). Each data then feed into neural networks for the classification task. The data is in an image-like array shown in Fig 4. for each task. Each task may have a pattern that can be learned by neural networks, even if there are not so clear differences between the classes. The figure data is taken as a sample from input to neural networks for 3 images to represent the input. In this study, we use 3 different models; CNN, LSTM, and Autoencoder.

4.3 Evaluation result

To determine the performance of the model used, a simple evaluation was conducted. The neural network will predict events that occur based on data in the form of images mentioned before. In this study, there are six types of events that exist. To determine the accuracy of the model prediction results, the prediction results of the model will be compared with the actual event. Furthermore, the number of correct predictions will be compared to all data entered into the model to be predicted and the percentage



(a) HandStart (b) FirstDigitTouch

(c) BothStartLoadPhase (d) LiftOff

(e) Replace (f) BothReleased

Fig. 4: Possible Pattern from Label

Table 1: Classification Result

Model	Accuracy
Auto Encoder	0.1613
LSTM	0.1653
CNN	0.1697

of success is sought. The result is shown in Table 1. The accuracy is represented by

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \quad (2)$$

5. Discussion

In this study, neural network algorithms were applied to decode 6 different tasks. While the results are quite low in accuracy to detecting tasks, this is due to the ignored artifact and the test subject dataset being different from the trained model. EEG has characteristics to be affected by the different subjects. On the other hand, this research suggests the possibility of a pattern from the EEG signal while doing tasks visualized in an image while the task was being done. In addition, this study suggests decoding EEG tasks using a low number of channels available in the market.

References

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[3] Luciw, M., Jarocka, E. and Edin, B.: Multi-channel EEG recordings during 3,936 grasp and lift trials with varying weight and friction, *Trans. IEICE*, Sci Data 1, 140047 (2014).