A study of analysis model using BCI for long-time

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Abstract. Recently, Brain-computer interfaces (BCIs) are attractive systems that reflect the intentions of the patient. BCIs is used to help patients with amyotrophic lateral sclerosis (ALS) that have difficulty communicating due to paralysis. With long-term use of a BCI, it is conceivable that a sensor may be affected by a physiological phenomenon, such as sweating. In addition, the state of the user's brain activity varies with his/her concentration levels. These factors reduce the classification accuracy of brain activity and can lead to unintended behavior from the user. We aimed to study the causal relationship between the operating time and classification accuracy in order to develop a learning model in which classification accuracy is maintained in the long term using BCI. Brain activity was recorded when performing the left or the right hand movement. As a result, brain activity during the task varies immediately after the onset of BCI use compared to later time points. We can thus conclude that the model created using EEG data obtained immediately after BCI use cannot discriminate the new data. Based on the above results, we need to update the learning model for long-term BCIs.

Keywords: Brain-computer interface (BCI), Motor imagery, Machine learning, Electroencephalography(EEG)

1. INTRODUCTION

Recently, there has been an increase in the number of patients with amyotrophic lateral sclerosis (ALS) that have difficulty communicating due to paralysis. The number of ALS patients has increased from 8,285 to 9,950 in six years. In addition, there are significant numbers of people who are unable to freely move their bodies due to external factors, such as traffic accidents, brain infarctions, muscular dystrophy, etc. Many such patients are unable to communicate with their caregivers or to take independent action. These patients are more likely to experience anxiety and stress. Brain-computer interfaces (BCIs) are attractive systems that allow patients who are unable to move to communicate. BCIs are systems that can be controlled by analyzing brain activity using techniques such as electroencephalography (EEG), near-infrared spectroscopy (NIRS), functional magnetic resonance imaging (fMRI), to determine the intentions of the patient. BCIs are machines with operating systems that allow communication without a need for body movements (Niels Birbaumer, 2006). BCI is used to rehabilitate patients with neurological diseases and to allow them to communicate with their caregivers. The goal of the above study was to improve the classification accuracy of brain activity measures during the operating time, which was short in the study. With long-term use of a BCI, it is conceivable that a sensor may be affected by a physiological phenomenon, such as sweating. In addition, the state of the user's brain activity varies with his/her concentration levels. These factors reduce the classification accuracy of brain activity and can lead to unintended behavior from the user. We thus focus on the operating time of the BCI with the aim of increasing the user's independence. We aimed to study the causal relationship between the operating time and classification accuracy in order to develop a learning model in which classification accuracy is maintained in the long term using BCI.

2. Methods

Here we describe the imaging procedure used to measure brain activity and relevant hardware.

2.1 Motor imagery

Motor imagery is the recall of a movement without moving one's body. It has been used for the rehabilitation of patients and the training of athletes and has similar effects on learning to actual exercise. In this study, we instructed the subjects to recall the movement of tapping one's hand on the armrest of the chair in the environment shown in Figure 2.1.

Figure 2.1: Image tapping

2.2 Measurement hardware

We measured EEGs using a Thought Technology Co., Ltd., ProComp Infiniti （Figure 2.2）. ProComp Infiniti is a machine that records EEGs when its electrodes are placed on the scalp. EEGs measured on the scalp record the sum of the post-synaptic activity nerves of the brain when the brain is active. Therefore, if many nerves are active, there will be more post-synaptic potential and we will observe larger EEG values. The ProComp Infiniti sampled EEG activity at a frequency of 256 Hz and used 4 electrodes for recording. In this study, EEG was recorded using 4 electrodes (Fz, Cz, C3, C4) chosen based on a previous study (Mohammad H Alomari, 2013; Chih-I Hung, 2005). We used the international 10-20 system with the left earlobe as a reference and the right earlobe as the ground. The layout of the electrodes is shown in Figure 2.3.

Figure 2.2: Procomp Infiniti

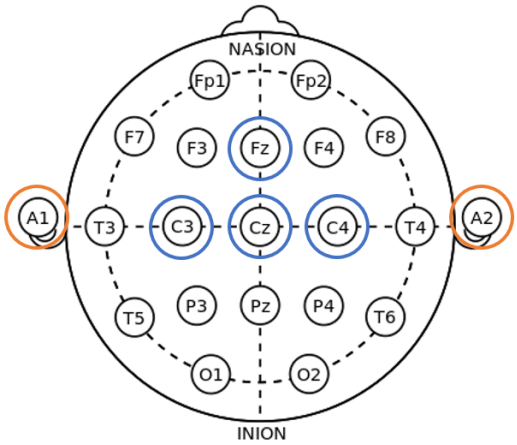

Figure 2.3: Electrode map

3. Experiment

This experimental study demonstrates how brain activity changes and classification accuracy is affected during the BCI operating time. Below, we describe the environment, the mental task, and our analysis.

3.1 Experiment environment

Five male subjects (A-E, four right handed and one left handed) 22-24 years of age participated in the experiment. Subjects performed the experiment sitting in a state that allowed the electrodes to be placed on their heads and on both earlobes. The experiment was performed in a dark room in which all electronic equipment other than the instrument (monitor, PC, BCI) was turned off.

3.2 Experimental task

The experimental task was designed based on previous studies (Pradeep Shenoy, 2006; Mohammad H Alomari, 2014). The experimental procedure is shown in Figure 3.1. The task consisted of the display of the rest symbol for 5 s, the display of the blank symbol for 2 s, and the display of the task symbol for 8 s (Figure 3.2). The above procedure comprises 1 trial. Each subject participated in 60 trials with breaks every 4th trial. There were two types of task screens. One consisted of a green square on the left side, while the other consisted of an orange square on the right side. The square position determines whether the left or the right hand should perform the tapping movement in the subject's imagination. During the experiment, brain activity was recorded at all times, except for the rest times.

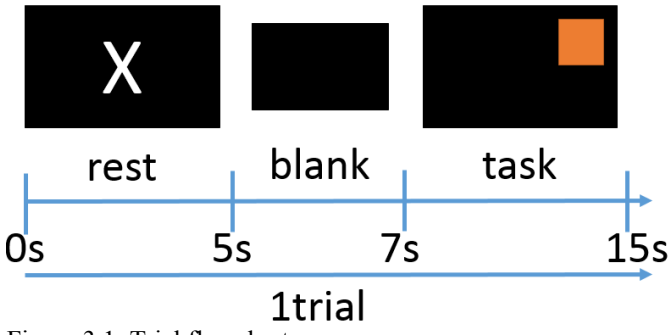

Figure 3.1: Trial flowchart

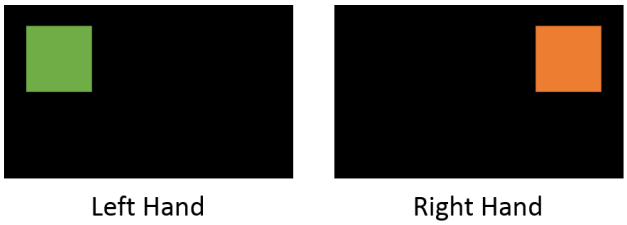

Figure 3.2: Task symbols

3.3 Analysis method

We performed a t-test to determine amplitudes that led to significant differences in the recorded brain activity. EEG data recorded at electrodes C3 and C4 were analyzed in the experiment. The summary of the analysis is shown in Figure 3.3. We applied fast Fourier transform analysis to brain activity data obtained in 15-s trials with window lengths of 1 second (256 Hz) and shift lengths of 0.5 s (128 Hz). We obtained data using an arithmetic mean between 8 Hz and 13 Hz. We performed a t-test on the data from the test group obtained during motor imagery trials 1-20 and calculated the p-value as shown in Appendix A. We were interested in the 10 lowest p-values obtained using these data. The classification of the data into the two classes was performed using an SVM grid search. The grid search was performed on 2 ^ 2 to 2 ^ 3 grids to analyze the cost parameter, the Radial Basis Function, and the kernel parameter. These parameters were selected to maximize the classification accuracy of group 1. EEG data were divided into three groups, with data from 20 trials in each group (group 1 consists of trials 1-20, group 2 consists of trials 21-40, and group 3 consists of trials 41-60). In addition, for group 1, we excluded data using the leave-one-out method and created a model outside of the data and performed discrimination analysis.

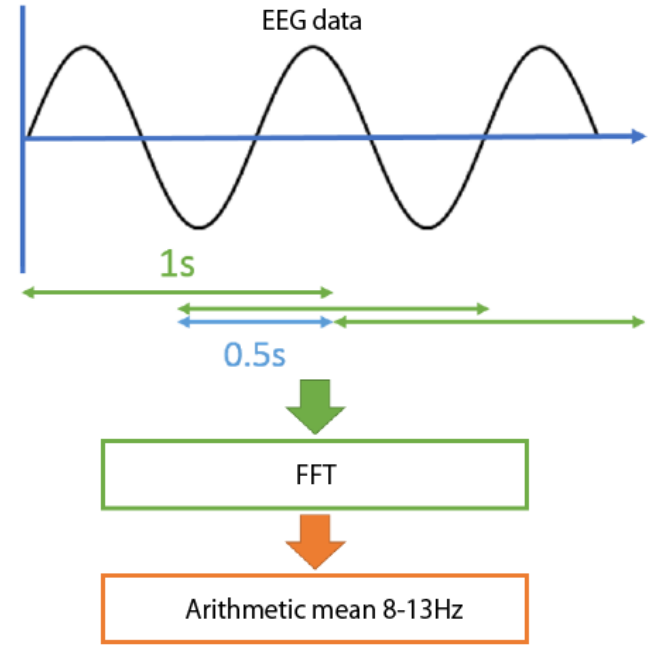

Figure 3.3: Analysis flowchart

4. Result

In this section, we describe significant differences observed in each data group and display the classification results using the learning model and data from group 1.

4.1 Significant differences in the data from each group

Appendix A shows the results of t-tests applied to EEG data from each data group. The figures consist of graphs of the variations in the significant differences found for each subject. Subject A is missing 256-Hz (1-s) data because some data was not recorded normally. However, the model obtained using subject A was made similarly to those for the other subjects. In group 1, the significant differences tend to appear during the task period (7-15 s). In contrast, in groups 2 and 3, the significant differences tends to appear during the blank period (5-7 s). As shown in this figure, the point at which the significant difference appeared in group 1 is not always the same as when the significant difference was observed in group 2 or group 3. In the next section, we will describe the effects of this tendency on classification accuracy.

4.2 Classification results

Figure 4.1 shows changes in classification accuracy for

all subjects in each of the data groups. The vertical axis indicates classification accuracy by SVM, while the horizontal axis indicates the data group number. We present data for subjects A-E. Group 1 accuracy is higher than 80% for all subjects, whereas group 2 accuracy decreases to near 50% for 4 of the subjects. Group 3 accuracy was even further decreased for 3 of the subjects, which indicated that it would be difficult to maintain classification accuracy using this model.

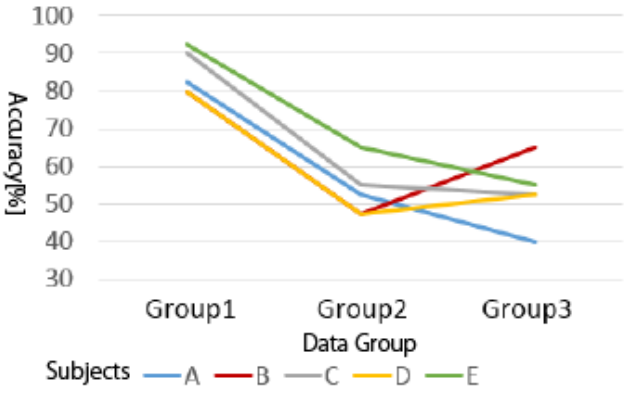

Figure 4.1: Classification accuracy

5. Discussion

The above results indicate that classification accuracy decreases in groups 2 and 3. We concluded that the model that used group 1 data was unable to correctly discriminate the new data. The cause of the decrease in the classification accuracy was thought to involve changes in brain activity levels and the fact that the subjects may have lost their concentration during the rest periods in the middle of the experiment. In addition, the relaxation of the subjects may also have been an important factor in the loss of classification accuracy. The significant differences were observed to change as the number of tasks increased. This enabled us to observe individual differences in the data. For example, the classification accuracy for subject ACE was further reduced in group 3, while the classification accuracy for subject BD was slightly increased. It is thus conceivable that significant differences may be observed again in later trials, as they did for subject BD. In addition, it is conceivable that we had over-fitting of the data with decreases in the classification factor, as EEG data was lacking. There is a possibility that the generalization capability of the model was reduced due to the use of an inappropriate number of data points in the 10-feature model, which could not correctly discriminate the new data. Furthermore, if the model continues to learn from the data in groups 2 and 3, the classification accuracy of the group 1 data may be reduced. Based on these factors, brain activity during the task is different immediately after the onset of BCI use compared to later time points. We can thus conclude that the model created using EEG data obtained immediately after BCI use cannot discriminate the new data. Therefore, there is a need to update the learning model when performing long-term BCI studies. In future research, we will investigate the causal relationship between operating time and classification accuracy in more detail with the aim of building a BCI that leads to the creation of a model that is able to select suitable data for the classification.

6. Conclusion

We aimed to study the causal dependence between the operating time and classification accuracy in BCI in order to develop a learning model that maintains its classification accuracy in the long–term. Our ultimate goal is to enable the user to have extended independence. We designed a task of motor imagery for use in the classification of brain activity. We instructed 5 subjects to recall the motor imagery of the left- or right-hand tapping movement when presented with the square. We used only EEG data from electrodes C3 and C4 and studied variations in brain activity. We then performed a t-test to test the group consisting of motor imagery data from trials 1-20. The model was created by selecting features that led to the 10 lowest p-values. We created three data groups by dividing the data into 20–trial blocks. When we analyzed the data using this model, group 1 accuracy was greater than 80% for all subjects, while group 2 accuracy was decreased to near 50%. As a result, the point at which the significant difference appeared in group 1 was not always the same at which significant differences were observed in groups 2 and 3. The cause of the decrease in classification accuracy was the change in the brain activity of the users during the rest period in the middle of the experiment. This may have led to over-fitting of the data, as the EEG data used to create the model was not present during this time. Based on the above results, we need to update the learning model for long-term BCIs. In future research, we will investigate the causal relationship between operating time and classification accuracy in more detail with the aim of building a BCI that creates a model that selects suitable data for better classification.

Appendix A. Subject's p-value

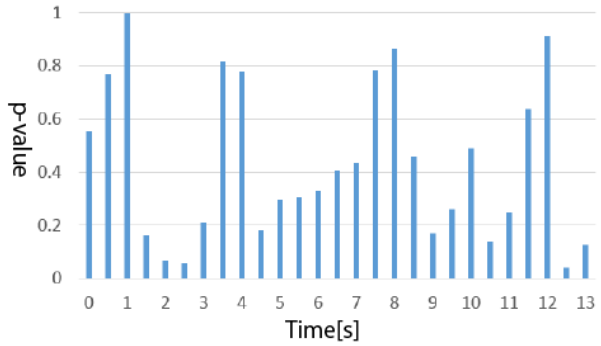

Figure A.1: Subject A of p-value in Group1

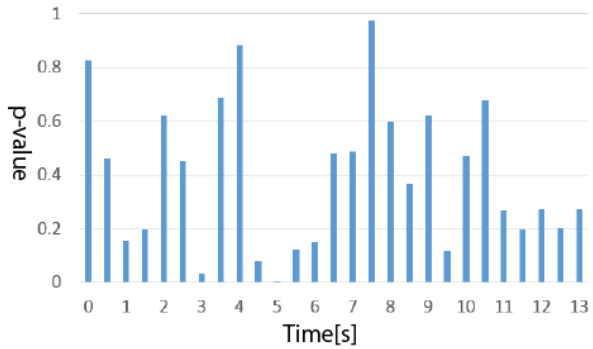

Figure A.2: Subject A of p-value in Group2

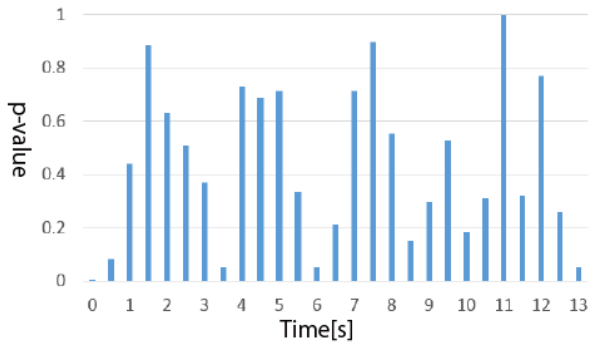

Figure A.3: Subject A of p-value in Group3

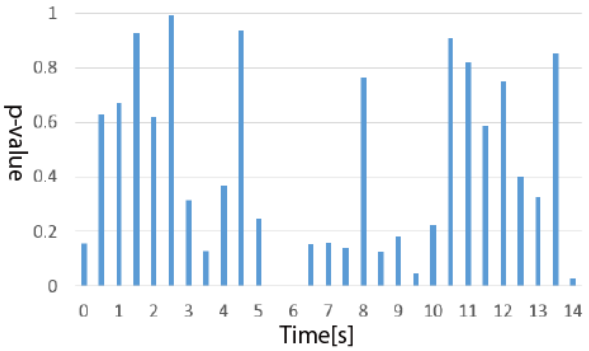

Figure A.4: Subject B of p-value in Group1

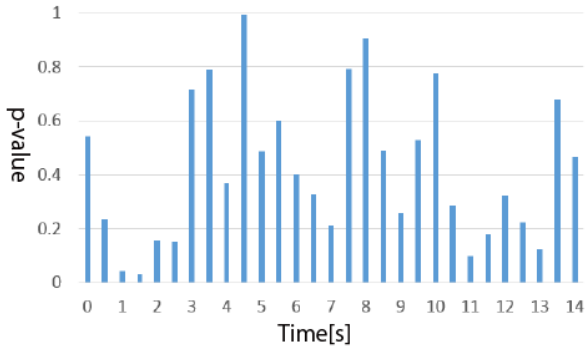

Figure A.5: Subject B of p-value in Group2

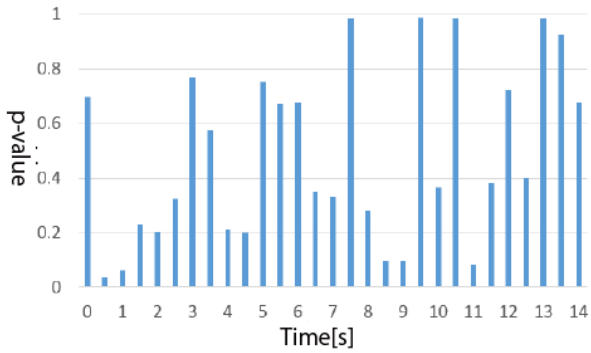

Figure A.6: Subject B of p-value in Group3

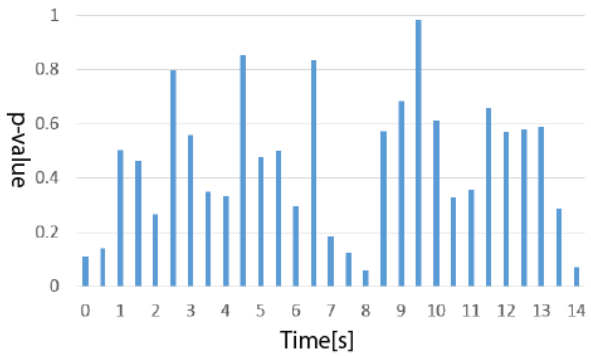

Figure A.7: Subject C of p-value in Group1

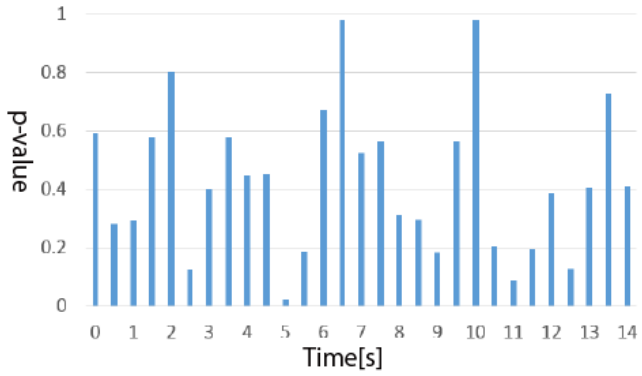

Figure A.8: Subject C of p-value in Group2

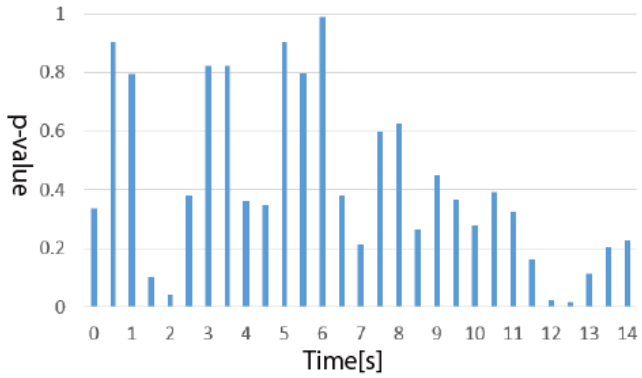

Figure A.9: Subject C of p-value in Group3

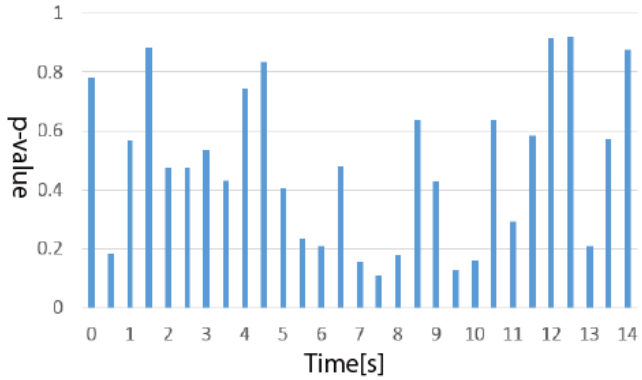

Figure A.10: Subject D of p-value in Group1

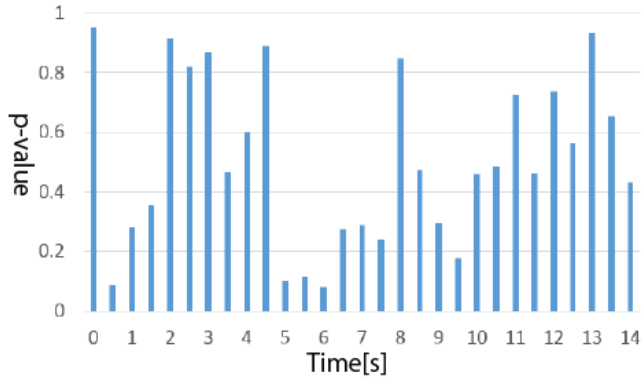

Figure A.11: Subject D of p-value in Group2

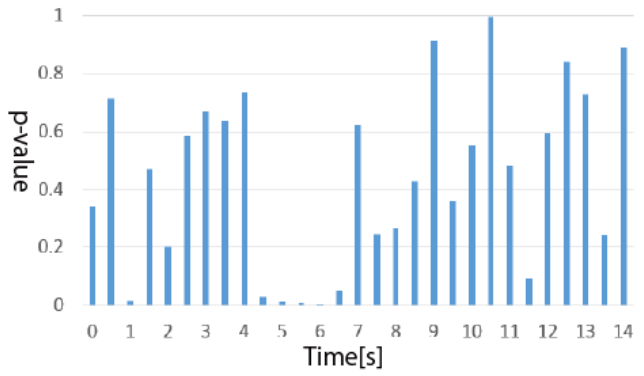

Figure A.12: Subject D of p-value in Group3

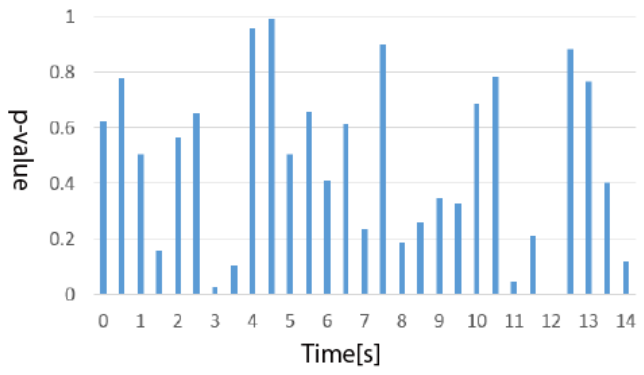

Figure A.13: Subject E of p-value in Group1

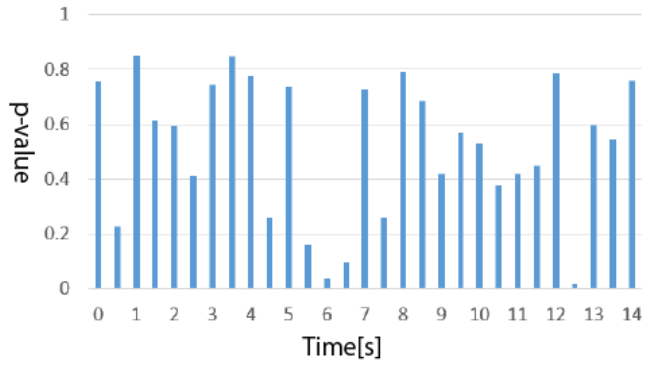

Figure A.14: Subject E of p-value in Group2

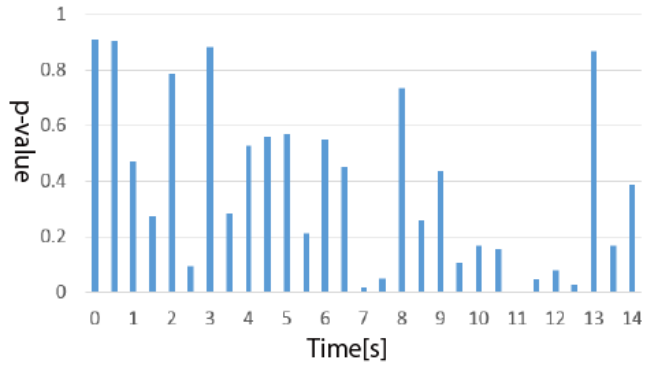

Figure A.15: Subject E of p-value in Group3

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