Master's Thesis
석사 학위논문

Subject-specific real time motor imaginary detection scheme for robot-aided hand rehabilitation

Raechang Chun(전 래 창 田 來 昌)

Department of Robotics Engineering

로봇공학전공

DGIST

2016

Master's Thesis
석사 학위논문

Subject-specific real time motor imaginary detection scheme for robot-aided hand rehabilitation

Raechang Chun(전 래 창 田 來 昌)

Department of Robotics Engineering

로봇공학전공

DGIST

2016

Subject-specific real time motor imaginary detection scheme for robot-aided hand rehabilitation

Advisor :	Professor	Jonghyun Kim
Co-advisor :	Professor	Sungho Jang

By

Raechang Chun
Department of Robotics Engineering
DGIST

A thesis submitted to the faculty of DGIST in partial fulfillment of the requirements for the degree of Master of Science in the Department of Robotics Engineering. The study was conducted in accordance with Code of Research Ethics[1)].

1. 8. 2016

Approved by

Professor (Advisor)	Jonghyun Kim	(Signature)
Professor (Co-Advisor)	Sungho Jang	(Signature)

[1)] Declaration of Ethical Conduct in Research: I, as a graduate student of DGIST, hereby declare that I have not committed any acts that may damage the credibility of my research. These include, but are not limited to: falsification, thesis written by someone else, distortion of research findings or plagiarism. I affirm that my thesis contains honest conclusions based on my own careful research under the guidance of my thesis advisor.

Subject-specific real time motor imaginary detection scheme for robot-aided hand rehabilitation

Raechang Chun

Accepted in partial fulfillment of the requirements for the degree of Master of Science.

11. 24. 2015

Head of Committee 김 종 현 (인)
Prof. Jonghyun Kim
Committee Member 장 성 호 (인)
Prof. Sungho Jang
Committee Member 장 평 훈 (인)
Prof. Pyunghoon Chang

MS/RT
201423006

전 래 창. Rae Chang Chun. Subject-specific real time motor imaginary detection scheme for robot-aided hand rehabilitation. Department of Robotics Engineering. 2016. 50p. Advisors Prof. Jonghyun Kim, Co-Advisors Prof. Sung Ho Jang.

ABSTRACT

This study is a motor imaginary detection scheme for rehabilitation. Recently, detecting motor imaginary movement based on brain mapping device has been applied to improve robot-aided therapy for rehabilitation. Our goal is to develop a simple method that perform a system in real time to make a natural movement, to build subject-specific real time code to realize a system that help subject-specific rehabilitation therapy and classify ERD and Fake MI and eliminate Fake MI for correct rehabilitation therapy. We opt to EEG for brain imaging modality and using Matlab software for EEG signal processing. Event-related desynchronization (ERD) occurs in specific frequency band in brain wave when human has intention of movement. To detect ERD, in this thesis, we utilize a method called Machine Learning. The machine learning algorithm we applied in this study was Support Vector Machine (SVM). The result of SVM represents low success trial of ERD and low false detection of Fake MI. The algorithm that remove Fake MI also eliminate the ERD and that cause low success trials. We built the real time system that be able to perform voluntary-like movement. During building the system, we have found problems like Fake MI. Fake MI is the factor that interrupt a correct rehabilitation therapy.

Keywords: Human intention, Motor imagery ,Voluntary movement, Event-related Desynchronization(ERD), Electroencephalogram(EEG), Support Vector Machine(SVM), Machine learning, Real time signal processing.

Contents

List of Figures

List of Tables

I. Introduction

1.1 Background

Recently, detecting motor imaginary movement based on brain mapping device has been applied to improve robot-aided therapy for rehabilitation. The main viewpoint of this approach is that connection between motor imaginary detection and robot-aided therapy be able to make voluntary-like movement with robot to the patients who have poor motor function. The majority of human movement is considered volitional. [1] Kornhuber and Deecke recorded EEG signals associated with human self-paced voluntary finger movement [2] and identified a slow, negative DC potential occurring as early as 1.5s before the production of the movement. Pfurtscheller et al. represented a short-lasting block/decrease of frequency power or event-related desynchronization (ERD) in the alpha band (8-12 Hz) [3] beginning about 2s before self-paced button pushing. Because the voluntary-like movement provides physical therapy as well as appropriate sensory feedback, it would be effective to maximize brain plasticity [4], which is a key part to recover motor function. Harnessing brain plasticity should make it possible to reconstruct the closed loop between the brain and the body. [5] Kawahira et al. proposed an effective rehabilitation method. [6] In their study, when the voluntary movement is performed, the patients receive the support from the outside. However, it is very difficult work for physical therapists to apply this method. Therefore, robot aided rehabilitation has been required. It provides a novel method to stroke patients may interact with external devices.

Hand rehabilitation is a typical target of this thesis. Given the central role that hand movements normally play in human existence [7-11], much attention in rehabilitation research has been focused on understanding and restoring hand motor function after stroke [12-14]. Moreover motor imaginary of hand is relatively simple because of the large motor cortex hand area of human brain.

Since we now want to voluntary-like movement, a processing time of signal should be as much as fast to connect between intention of human motion and movement by robot. This is for natural movement. If we do not have a proper processing time, it causes a human intention and movement mismatch. So subject feel uncomfortable and learn a false motor learning. For that, we should build a system in real time. We need a real time signal processing step and data transferring. In this study, we use a MATLAB programing tool for real time system. All processing steps and data transferring are performed in MATLAB.

In this thesis, we opt to EEG for brain imaging modality. Since EEG has high temporal resolution compared to other modalities, such as fMRI and fNIRS [15], it can detect human brain signal in real time. Thanks to EEG, the patient can mimic voluntary movement by using robot that is triggered by motor imaginary, and thus the patient's motor control loop is realized with vision and proprioceptive feedback properly. For that, real-time and fast detection of motor imaginary is required to implement voluntary-like movement by using robot. EEG signals are transferred to the PC using MATLAB.

Also, brain signal patterns are different from every subjects and each trial. EEG signals have a subjectivity. We need a subject-specific method. It is important to build a suitable system for patients. Usually, event-related desynchronization (ERD) occurs in specific frequency band and that frequency band shows a few difference among subject. In other words, there are optimized frequency band each subject. To find a frequency band, we use ERSP graph. ERSP graph shows decibel value with respect to time according to frequency in one channel. We referred the ERSP graph but the graph shows a statistical result so it may be discrepancy between ERSP graph and raw data.

ERD appear with different pattern by each subject and by each trial. That is a complicated problem. Because patterns do not uniform, we cannot set a proper reference. So in this thesis, we utilize a method called Machine Learning. The machine learning algorithm we applied in this study was Support Vector Machine (SVM). In machine learning, support vector machines are supervised learning models with associated learning algorithm that analyze data and recognize, used for classification and regression analysis. Given a set of training examples, each marked for belonging to one of two categories, and SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. Because SVM classify a data set and recognize, we can utilize this method for interface with robot. SVM has an advantage about real time data analyze because real time data is as fast as sampling magnitude. So person cannot recognize and classify a data set. Also human's decision about data classification has subjectivity and was not fast to catch a feature, ERD. SVM can produce a quantitative and constant reference about data set. It is suitable for handling a data that has subjectivity. In this study, we propose a system that applied support vector machine.

Existing studies on motor imagery detection has several limitations. Most of them did not focused on rehabilitation but brain-computer interface (BCI) [16]. Those studies did not subject-specific elements such as frequency range of brain wave. Frequency range is important for patient to detect a motor imagery. For analyzing EEG brain signal, some studies used generalized frequency range of brain wave without consideration of the patient's characteristic. [17, 18] In [19], a method, common spatial patterns (CSP) is used for EEG analysis. An advantage of the CSP method is that it does not require a priori selection of subject-specific frequency bands. However, that method needs a large number of electrodes. It is not suitable for clinical use. Besides, some studies have a post processing procedure not a real time processing method. [20] Also, most of studies performed analysis only duration of trial. That did not consider a duration between trials. The reason was that they only concentrated on an accuracy of trial so they didn't need to analyze a duration between trials. However, this thesis was about voluntary movement and there was not any external cue to divide a duration of analysis. We need to analyze the duration between trials to detect an exact movement trial.

We propose a scheme that can detect subject-specific real time motor imagery for robot-aided hand rehabilitation. First, this study will focus on a patient-specific method. To satisfy such a performance, we will apply machine learning scheme. Second, this study will develop an improvement of performance of system's real time. For that, we will build up a simple algorithm to reduce a delay. In our knowledge, most of studies have a post-processing method. Although in case of real time, a method is different from our study. [21] We suggest a scheme that process data in real time. Third, this study will concentrate on an analysis of duration between trials. This is for detection of an exact voluntary movement. For that, we need to classification of characteristic of trial and between trials.

1.2 Contribution Point

There are three contribution points in this thesis. First is to build a system to give a voluntary-like movement to subject. To realize the system, we set up a protocol without external cue and eliminate an element that can detect false movement trial. That means there is a potential to detect false decision unintended because we analyze the movement trial and duration between trials. We call it as Fake MI. Fake MI is a false intention contrast to subject’s voluntary movement. Because Fake MI is similar to ERD pattern that occur in movement trial. The reason why Fake MI is important issue is that it causes false rehabilitation learning to patient and false proprioceptive and feedback loop. So we need to eliminate the Fake MI to detect an exact voluntary movement. The method will discuss later.

Second is the subject-specific. As we mentioned before, brain wave has subjectivity so it has different characteristics for each subject. Also optimized frequency band need to find ERD pattern because ERD occur in specific frequency band but the band is a little bit different each subject. Moreover, to apply the support vector machine, subject-specific method is useful to maximize an applicability of subject because we use subject’s data to utilize the support vector machine.

Third is the reduction of electrode used. In this thesis, we only use selected electrode to analyze brain wave data. Although, we need a full electrode for the first time to select electrode to use. This is for acquisition of data from initial phase. Next time from initial phase, we only use selected electrode to execute the real time system. This point has a good advantage to reduce set up time and make good applicability.

These are the contribution points of this thesis. To our knowledge, there is no study to research points that mentioned above simultaneously, especially Fake MI. The research of Fake MI has not been reported not yet. In this sense, this study contribute new points that have never been studied before.

1.3 Purpose

The aim of this study are 1) to develop a simple method that perform a system in real time to make a natural movement , 2) to build subject-specific real time code to realize a system that help subject-specific rehabilitation therapy and 3) classify ERD and Fake MI and eliminate Fake MI for correct rehabilitation therapy. For that, processing step was built as simple method to reduce processing time for voluntary-like movement. Protocol was set to mimic a movement or motor imagery of stroke patient. We will develop a system based on EEG. EEG is a useful device that can measure brain signal in real time. It also benefits to detect an intention of human's movement before movement. This is also for voluntary-like movement. To build a subject-specific real time code, we made the code for each subject respectively. We adjusted subject-specific parameter such as frequency band and used electrode and so on. To classify ERD and Fake MI, we use multi-channel method. By analyzing multi-channel as flow of time, we can distinguish ERD and Fake MI. From that method, we can find the Fake MI feature and eliminate it. We can realize a voluntary movement only if Fake MI was eliminated.

II. Method

2.1 Participant

5 healthy subjects (Male : 4 , Female : 1) participated in our study. All participant recruited from students of Daegu-Gyeongbuk Institute of Science and Technology. This experiment was for healthy subject so in this study inclusion and exclusion criteria was not existed. Table 1. Shows a list of healthy subject participated in the experiment. All participant have no neurological disorder.

Table 1. List of healthy subjects that participated in the study

N	Sex	Age [y]
4	M	27.75
1	F	24

2.2 Device

The study was needed two devices. Electroencephalogram(EEG) and electromyography(EMG) was used for this study. EEG is an electrophysiological monitoring method to record electrical activity of the brain. It is typically noninvasive, with the electrodes placed along the scalp. We used noninvasive EEG consisted of 32 electrodes. EEG product came from Brain Product, Inc. The devise consisted of electrode, amplifier, battery pack and splitter box. Sampling rate is 500 Hz and acquisition program showed a brain wave signal in real time and it can input announcement by making user-friendly. Also trigger signal was shown in that program. EEG measured voltage fluctuations resulting from ionic current within the neurons of the brain. EEG referred to the recording of the brain’s spontaneous electrical activity over a period of time. In this thesis, we opted to EEG for brain imaging modality. Since EEG has high temporal resolution compared to other modalities, such as fMRI and fNIRS. This device can detect human brain signal in real time. On the other hand, EEG has a low spatial resolution so we cannot know correct location that brain wave is activated. Moreover, voltage is measured from

EEG so it is difficult to find an exact location. For higher spatial resolution, we use 128 channel cap. The cap has 128 channel spot so we can utilize a variety of brain area and find more precise location or more activated brain wave. Figure 1 shows EEG cap covered on head and electrodes. Figure 2 shows a whole EEG devices including Amplifier, Adaptor, ACTICAP, electrode, battery pack and DAQ board. DAQ board is needed for sending trigger signal. The device is connected to EMG device.

Figure 1. EEG Cap and Electrode

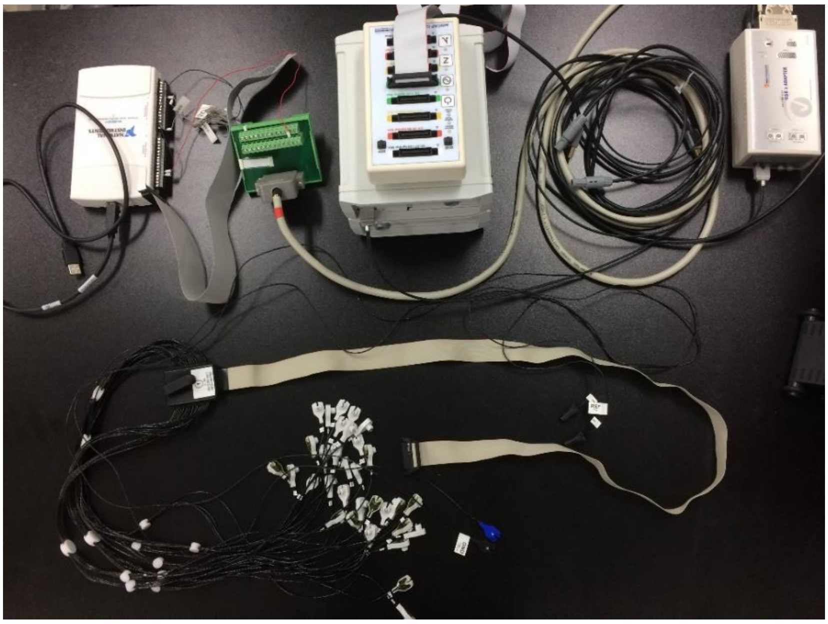

Figure 2. Amplifier, Adaptor, ACTICAP, electrode, battery pack and DAQ board

Electromyography (EMG) is an electrodiagnostic medicine technique for evaluating and recording the electrical activity produced by skeletal muscles. (Fig 3.) EMG is performed using an instrument called an electromyography to produce a record called an electromyogram. An electromyography detects the electrical potential generated by muscle cells when these cells are electrically or neurologically activated. In this thesis, EMG is used to send a trigger signal to EEG device so EEG acquisition software record a time that subject's muscles are activated. This is needed for exact time to movement. Because intention of human motion is voluntary movement, there are no defined duration or time to detect a motion intention. We need a method that detect a movement and decide to use EMG device using human muscle's activation. This device is a gold standard about movement time.

Figure 3. Electromyography (EMG)

2.3 Experiment protocol

2.3.1 Surroundings

Subjects were seated in a chair with the forearm supported by armrest. They were asked to perform a self-paced voluntary movement task of hand extension. There are no external cue of movement time. That’s why we use EMG for trigger. They were especially asked not to count time and were asked to make the movement whenever they wanted to. And subjects were asked to keep all muscles, asked to remain relaxed between any two continuous movements. Body adjustments, throat clearing and other movements were to be avoided. Because EEG device is sensitive to movement noise. So if subjects moved their upper body a little bit, a wire connected to electrode was moved by upper body or head. It caused noise by fluctuating raw data. Experiment place was the corner of the laboratory for excluding sounds and other disturbance. Surroundings were set to reduce any disturbance that can affect to subject. It is essential to prevent artifact. Figure 4 shows the surroundings of EEG experiment.

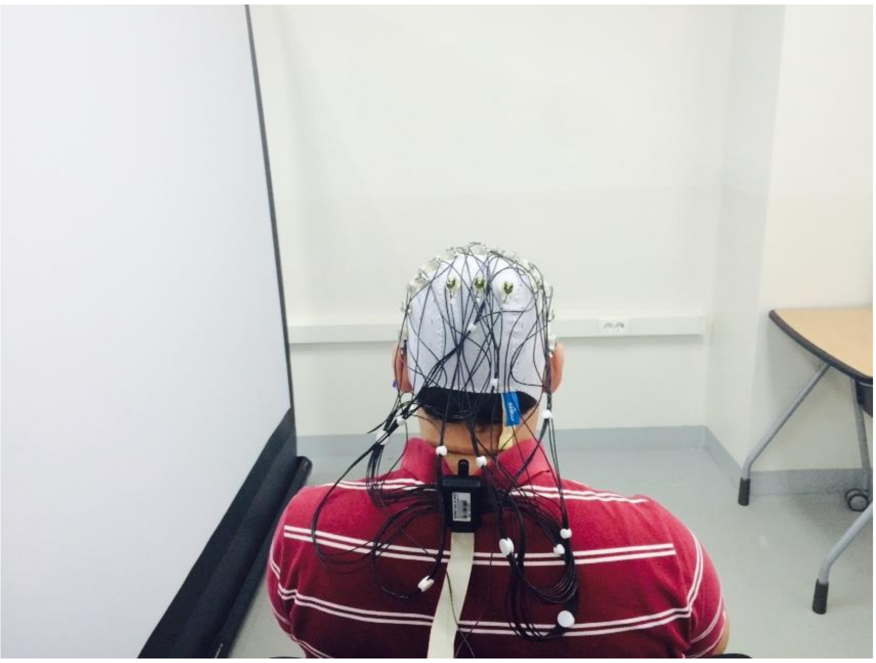

Figure 4. Surroundings of EEG experiment

2.3.2 Experiment setup and protocol

In the experiment, EEG and the spontaneous motion of hand extension were measured simultaneously from five healthy subjects. The configuration of the experimental setup is shown in Fig 5. EEG was measured using electrode connected to ACTICAP from 32 scalp sites. Electrode position is shown in Fig 6. 10-20 international system was applied to the cap and the reference electrode was placed on the left ear and the ground electrode was placed on the AFz site. The electrode positions were over the primary motor cortex area (Right and Left) and supplementary area (SMA). Primary motor cortex is related to hand movement and SMA area has a potential about motor imagery. We decided to cover SMA area. The brain wave signal was monitored through acquisition software. EEG signals are transferred to the target PC using MATLAB. The target motion was hand extension but in this thesis it was not actual movement. We covered the subject’s hand with band to prevent actual movement. Exactly speaking, it was constraint movement. In order to limited motion, we didn’t know a definite movement because of not actual movement. Only one thing that we know was muscle activation by subject. The reason why we bind subject’s hand is to close patient’s circumstance. A patient with stroke has poor motor function. They try to move their hands but it is not easy task. So we applied constraint movement to healthy subject to give a surroundings that patients may have. Fig 7 (a), (b) shows experiment setup. Total trial was 30. The longer trial caused subject’s fatigue and low muscle’s activation.

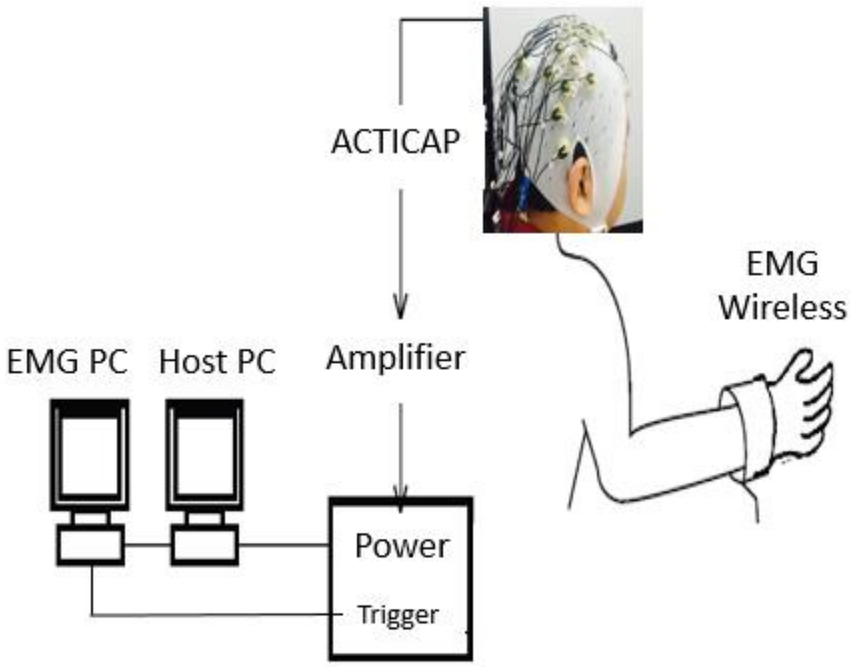

Figure 5. Overall configuration of the experimental setup

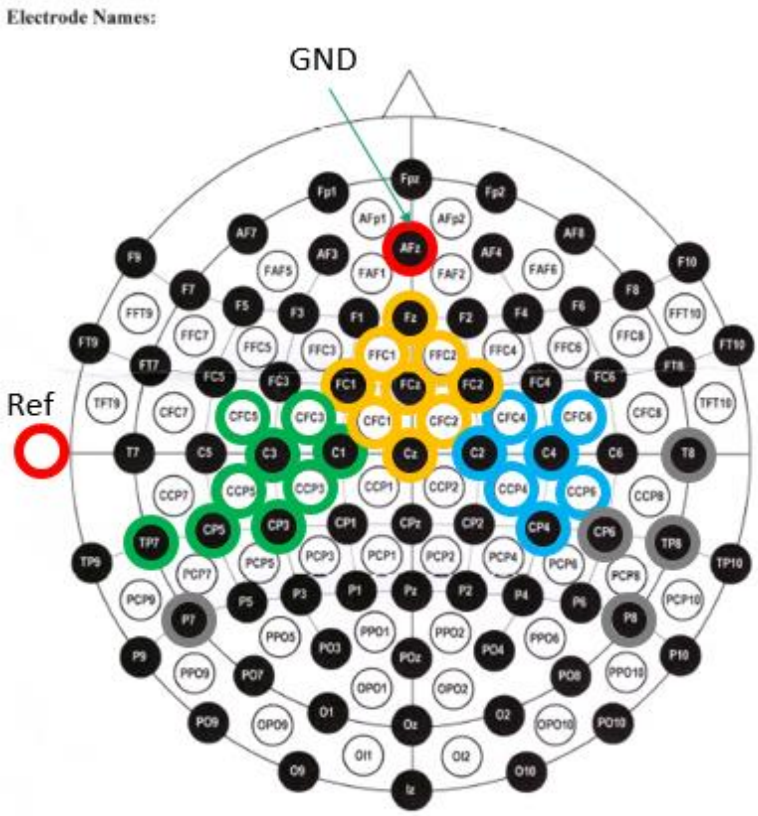

Figure 6. 10-20 International System and Electrode position

Figure 7. (a) , (b) Experiment setup

The measurement for a single trial is performed in the following procedure.

1) EEG cap was put on subject's head according to 10-20 International System

2) The 32 electrodes were placed on the scalp sites of the subject.

3) The hand of the subject was bound with strap to make a constraint movement.

4) The subject tried to perform a hand extension with limited action whenever they want

5) Successive trial was continued until 30^{th} trial. There was no fixed time between trials.

Experiment plan was represented in table 2. Three times of EEG experiment was performed to all subjects with same protocol.

Table 2. EEG Experiment date

	Sub1 M	Sub2 M	Sub3 M	Sub4 F	Sub5 M
Ex1	7/9	9/14	9/16	10/1	10/6
Ex2	7/23	9/21	9/23	10/5	10/7
Ex3	9/1	9/30	9/30	10/7	10/28

2.4 System Configuration

The overall step was performed in the following procedure. [22]

1) EEG is measured

2) EEG data acquisition (Real Time)

3) Signal processing (MATLAB)

4) Filtering

5) Machine Learning (SVM)

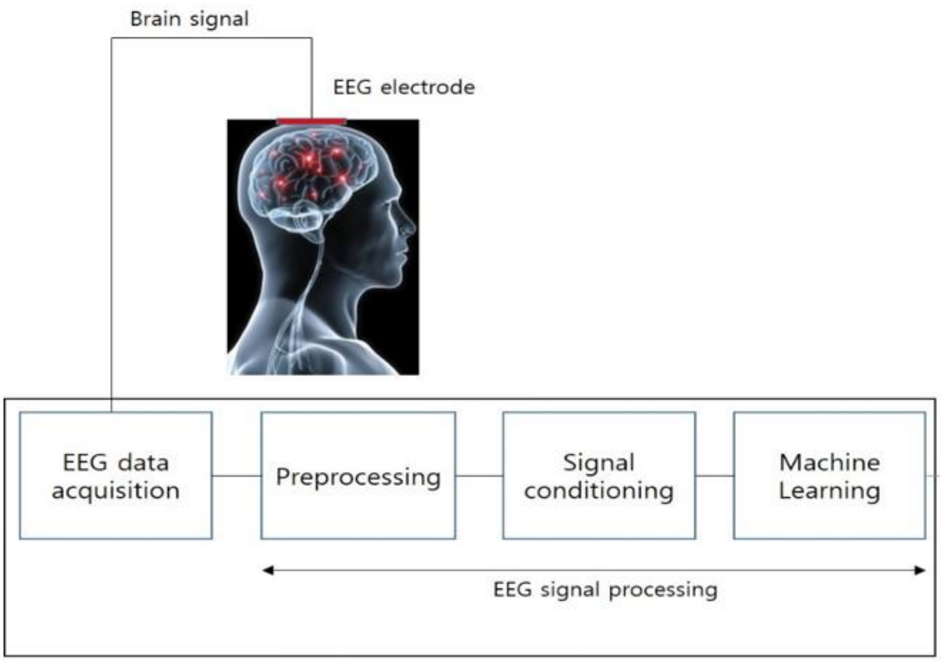

Figure 8. System Configuration

First, we measured a brain wave through EEG. And then, the signal was monitored by EEG data acquisition. Software program was linked to MATLAB. The MATLAB code was for real time signal processing. The code transferred the EEG data from Recorder, acquisition software, in real time to another software such as MATLAB. Next was pre-processing. This step performed brain wave signal processing to find ERD pattern. ERD was not reveal under a condition of time independent graph. Because ERD has frequency components, especially specific frequency band, ERD reveals in frequency domain. So Fourier transform to convert time domain to frequency domain is needed in this step. And then, signals pass a filtering step before machine learning step. The reason why this filtering step is needed is to distinguish a data during rest and during trial and transfer ERD-like data to machine learning. So machine learning classify and recognize the data whether this data set is movement that has human intention, that is, this data set is ERD or not. If there are no filtering step, machine learning is performed continuously and this work give a much burden to system. Filtering give an efficacy of system and affect an accuracy of SVM. Machine learning step is a final procedure of system. In this step, computer can classify and determine what data set are ERD, that is, movement that has human intention. And if SVM determine the data set is true, finally computer show a result on the screen. That is preparation of controlling a hand rehabilitation robot. Next chapter show a detail.

2.4.1 Signal processing

Signal processing step was performed in MATLAB code. The code performed a Fast Fourier Transform (FFT). A fast Fourier transform algorithm computed the discrete Fourier transform (DFT) of a sequence, or its inverse. An FFT computed the DFT and produced exactly the same result as evaluation the DFT definition directly. Let $x_0, \ldots, x_{N-1}$ be complex numbers. The DFT is defined by the formula.

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i2\pi k \frac{n}{N}} \qquad k = 0, \ldots, N-1.$$

The most important difference with DFT is that FFT is much faster. So we apply this method in system. Because we pursue a fast signal processing system for realization of voluntary-like movement. It should be avoided that system was delayed. It was a preprocessing to detect ERD.

After passing fast Fourier transform, it was given a power spectrum in frequency domain. Frequency range is a half of EEG data acquisition software sampling time, 250Hz. The MATLAB code shows a power spectrum graph every instant that takes code processing time. Code processing time is 100Hz. So the graph appear every 0.01 seconds. In the graph, we used only specific frequency band because ERD occurred in that area. To detect ERD, power spectrum was calculated by mean value of specific frequency band. This specific frequency band is different by subjects. It is needed to find an optimized frequency band. If a frequency band is shifted a little bit from optimized area, ERD pattern may not occur.

By observing the mean value with respect to time, ERD appear at the time of movement. Fig 9 shows a time history of the mean value of the specific frequency band, as a function of time from the electrode on C3. That graph appear ERD and usually occur before onset of movement. We verified a strong negative slope in the graph and if it was detected such a pattern, we can recognize a human intention of movement and build a detection scheme.

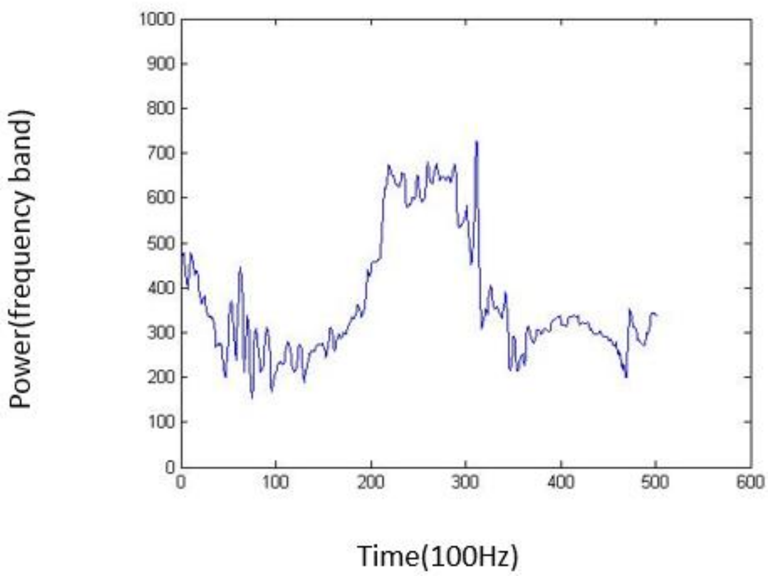

Figure 9. Time history of the mean value of the specific frequency band

In this thesis, that kinds of graph means that the onset time of the constraint movement is coincided with time Time=500 [Hz]. That is, the end of graph is the onset time.

By passing through, signal processing, it can be verify and detect ERD pattern. This ERD pattern was just one of many different ERD pattern. The pattern was observed as many kinds of pattern and occurred as different pattern by each subject and by each trial with same subject. That means ERD pattern has subjectivity. We should reduce this subjectivity not to recognize false ERD pattern or to detect an exact ERD pattern. Because of voluntary-like movement was performed in this study, there was no external cue in experiment procedure as we mentioned before. That means we cannot know when subject did movement and brain wave signal should be always processed in order not to know a movement time. As analyze duration did not exist, the system has a potential to detect false ERD pattern. Therefore, classification method is essential to this system. We dealt with this topic in next chapter.

After signal processing step, filtering step was performed. In filtering process, it was decided which data was transferred and the data was transferred to machine learning process. It act as a trigger to send a data to next step. Filtering did not designed a complex structure. If the filtering has a high threshold, SVM part was reduced and it should be avoided. It just took a simple role to transfer a data to next step. If filtering step does not exist, the data was always sent to machine learning process every time that the code is execute. So it gave a much burden to the system. Filtering process is needed to reduce system's burden.

2.4.2 Machine learning

In this thesis, we applied a machine learning method to classify ERD pattern. Classification of ERD patterns is difficult for human to distinguish in order that ERD has subjectivity. It can be hard to recognize and classify ERD because of what the distinguish factors are. The machine learning algorithm we applied in this study was Support Vector Machine (SVM) and provide solutions to this problem by learning to recognize patterns from training data. In machine learning, support vector machines are supervised learning models with associated learning algorithm that analyze data and recognize, used for classification and regression analysis. Given a set of training examples, each marked for belonging to one of two categories, and SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier.

As our SVM classifier, we used LIBSVM, a library for SVMs. [22] To utilize LIVSVM, we need training data. Training data that consisted of specific format have a known classifications and should be formatted into a text file and that data was used to train a SVM. After that, SVM can classify other test data with unknown classification by comparing the data. [23]

SVM can efficiently perform a non-linear classification and linear classification. More formally, a support vector machine constructs a hyperplane or set of hyperplanes in a high or infinite dimensional space, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training data point of any class, since in general the larger the margin the lower the generalization error of the classifier. Fig 10 shows a picture of concept of support vector machine. We used linear classification method for this system.

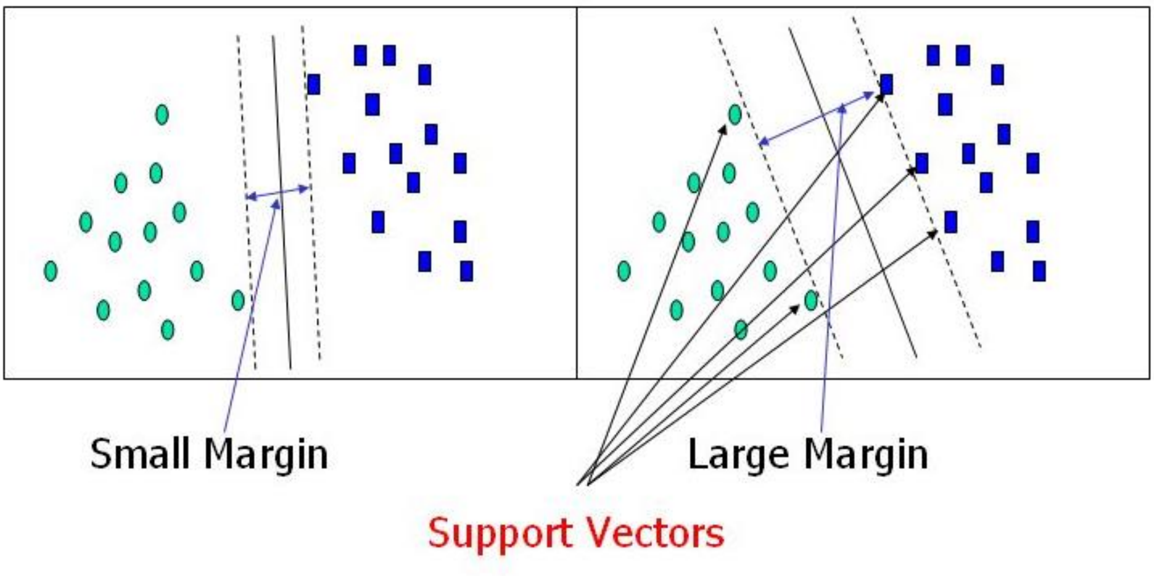

Fig 10. Picture of concept of support vector machine

To apply support vector machine, first feature extraction step was performed to extract a feature for classification. To extract a feature, we used a data processed that showed ERD pattern. After receiving the data, in machine learning feature was usually extracted from original data that can classify or distinguish a data compare to the other data. However, we only used original data not extracted data. Because of ERD patterns have subjectivity, feature was not distinguished and quantitative and routine value. And ERD patterns have many types of pattern so some representative data that can be reference pattern should be used. A data that shows ERD pattern was utilized for feature extraction not any processing step. A size of data may be changed for better performance. A reference of false ERD pattern was extracted from rest circumstance in EEG experiment that has a potential for not ERD pattern. Training data was made as text file. Fig 11 represented ERD patterns that used as reference data, that is, these patterns was used as true ERD pattern.

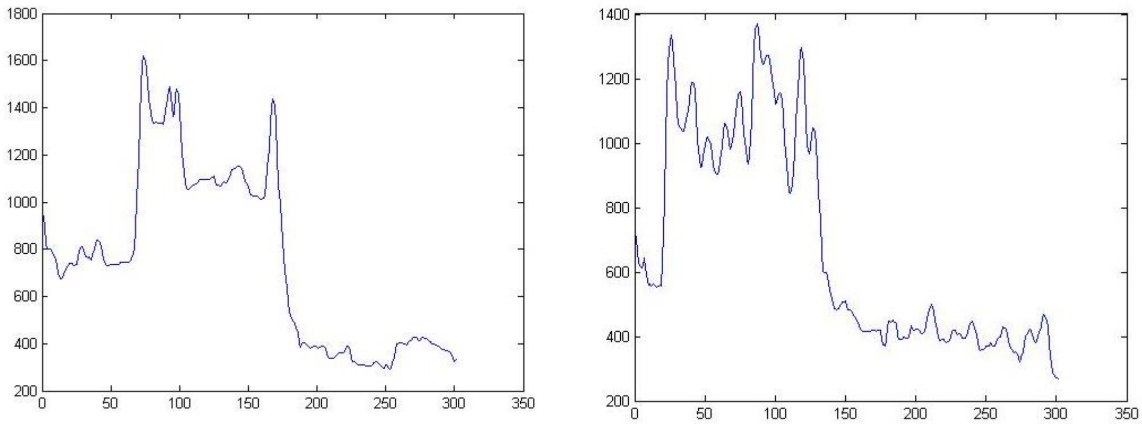

Figure 11. ERD patterns for reference data

Next, reference data was trained by machine learning, SVM. These data was used to compare with new data to test and classify pattern. To train SVM classifier, we made a training file and model file using LIBSVM. Training data must consist of specific format for using SVM. Fig 12 represents the specific format. The first column represents a classification index that means reference index to reveal true ERD pattern, 1 means true and 0 means false. From next column, numbers are given to data like a picture below.

```
1  1:687.043884  2:687.776306  3:684.609802  4:683.503052  5:683.608582  6:686.997375
1  1:715.154175  2:757.257935  3:774.898682  4:773.088379  5:751.027405  6:706.561646
1  1:646.142151  2:646.425293  3:648.965088  4:653.858948  5:663.313782  6:671.198608
1  1:1443.552490  2:1445.854248  3:1442.541260  4:1426.453979  5:1404.358643  6:1399.
1  1:679.675781  2:680.094666  3:676.505432  4:675.310425  5:675.476318  6:678.557617
1  1:1025.159790  2:1031.472168  3:1030.945068  4:1028.903320  5:1028.655029  6:1028.
1  1:786.842468  2:776.919739  3:743.616089  4:721.185364  5:725.968567  6:766.446350
1  1:661.577942  2:665.250366  3:659.697937  4:658.405762  5:653.882446  6:653.935730
0  1:587.132507  2:583.622375  3:566.439331  4:567.039978  5:584.723511  6:601.558960
0  1:514.906921  2:511.661224  3:511.479797  4:515.690125  5:515.181641  6:509.326324
0  1:591.284241  2:558.701782  3:549.970520  4:557.531250  5:572.511597  6:590.186768
0  1:704.671997  2:750.405823  3:798.486206  4:813.887939  5:804.884888  6:789.439941
0  1:505.569336  2:556.963501  3:648.405945  4:735.383179  5:788.949036  6:796.185669
```

Figure 12. Specific format to make a modeling of SVM

The first data of ERD pattern was given to number 1 and next data was given to number 2 and numbers are given step by step until size of data. That format should be followed the rules to execute SVM. So before running the real time code, training step was needed for that. After execute training file, we get a parameter of modeling file. The first problem was to decide which SVM kernel function to use. The LIBSVM that we apply, provide 4 kernel functions: linear, polynomial, radial basis function and sigmoid. Because of two classification index we need, linear kernel function was chosen in this support vector machine. After training data was trained in SVM, we can get a model file. Fig 13 shows a parameter resulting from executing training file.

```
optimization finished, #iter = 30
nu = 0.000000
obj = -0.000001, rho = 6.844232
nSV = 6, nBSV = 0
Total nSV = 6
```

Figure 13. Parameter resulting from executing training file

To apply SVM in the system, we first trained and made a training file ahead of executing real time MATLAB code. For that, we utilized an executed file programing already done and this file was set to execute in real time code. When we try to apply SVM method in real time code. Its processing time was too long so we cannot build real time system. To solve that problem, SVM executing file was used before running real time code. The method was that training file was made and trained using SVM executing file in advance and then when we run the code only test step was performed through compiled SVM file. It can reduce processing time completely compare with previous method. So long as data was passed filtering step, machine learning step was performed immediately so we can send a signal as fast as we can in addition classification was done that the signal is true or not.

2.4.3 ERD / Fake MI classification

As we mentioned above in introduction section, one of thesis contributions was ERD and Fake MI classification. The definition of Fake MI is a false ERD pattern that occur during rest time. That means false intention of human’s movement can be misjudged because of Fake MI. It is not related to movement but its pattern is similar to ERD so SVM can be confused by them. Fig 14 represents a Fake MI. In the figure, Fake MI pattern is similar to ERD pattern. It causes confusion to system, machine learning. Usually, Fake MI appear between trials of intention of human’s movement. Fake MI is not intent to move contrast to subject’s voluntary movement. The reason why Fake MI is important issue is that it causes false rehabilitation learning to patient and false proprioceptive and feedback loop. And this there is a potential to mislead a false rehabilitation therapy to patient. As a result, we should classify this Fake MI and ERD to reduce and eliminate the Fake MI.

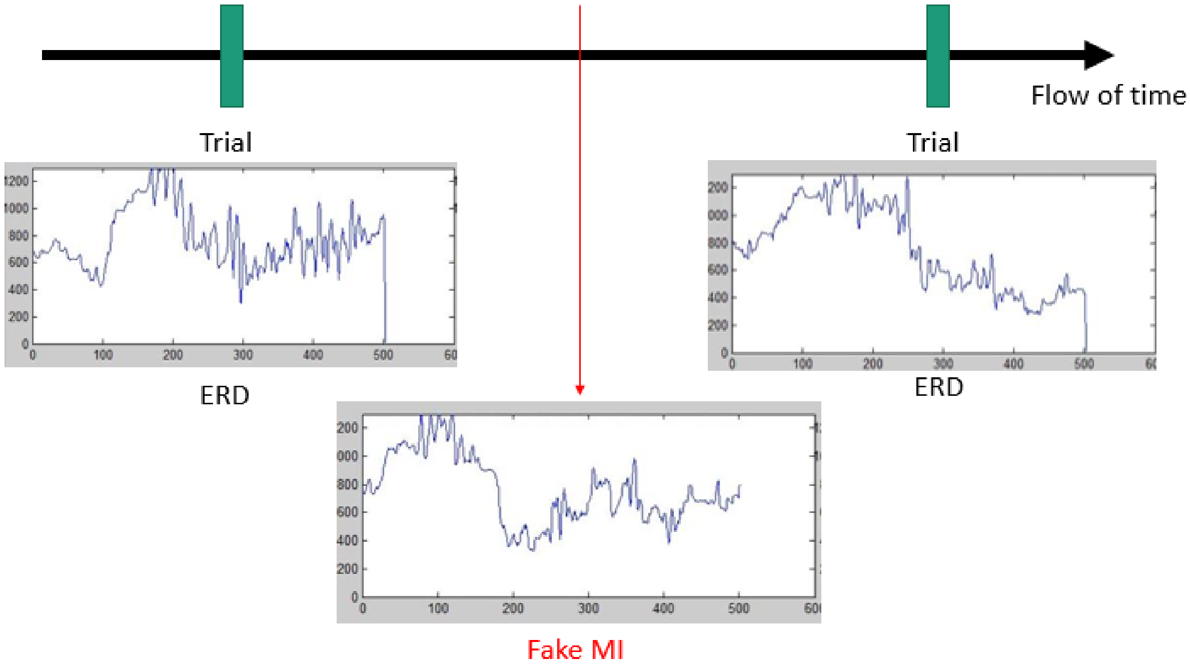

Figure 14. Definition of Fake MI

The first thing to classify Fake MI and ERD was to find the cause of appearance of Fake MI. In EEG experiment, we divided brain area according to BRODMANN area. BRODMANN area is region of the cerebral cortex in the human or other primate brain, defined by its cytoarchitecture or histological structure and organization of cells. And electrode position was also determined by BRODMANN area. Fig 15 shows a BRODMANN area when imagination of action was done. The most related and important area is the Primary Motor Cortex. That area is a brain region that in humans is located in the dorsal portion of the frontal lobe. At the primary motor cortex, motor representation is orderly arranged from the toe to mouth along a fold in the cortex called the central sulcus. Hand is included in this area so we positioned electrode in this area.

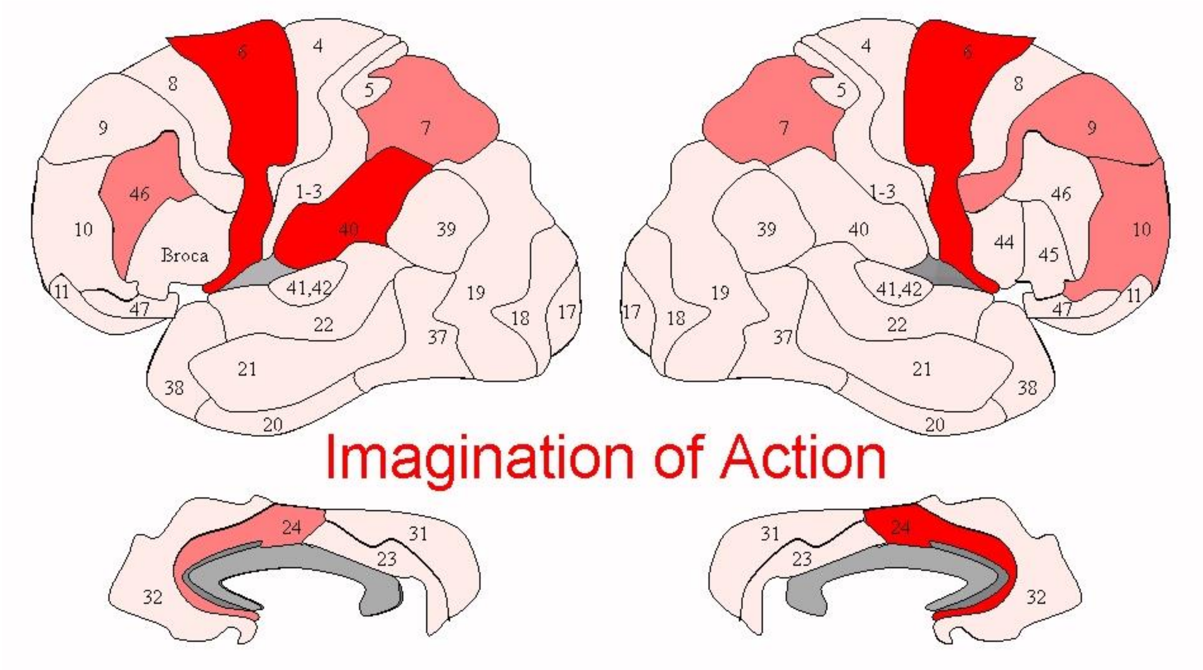

Figure 15. BRODMANN area when imagination of action was done

Each cerebral hemisphere of the primary motor cortex only contains a motor representation of the opposite side of the body. Therefore, in left and right primary motor area left is the region of interest because in experiment subject's right hand was bound. Other area was determined to check a potential to detect ERD pattern. SMA is an alternative area of primary motor cortex. Because unlike a healthy people, patient's brain is different from healthy in order to be damaged their brain. So primary motor area dose not working well. SMA is an alternative method to substitute primary motor area. The non-ROI is the region of irrelevant of intention of human's movement. This area need to classify Fake MI and ERD. The reason was explained in next paragraph.

In this study, we have checked a single trial ERD pattern to verify Fake MI according to primary motor, sensorimotor and non-ROI. By checking the Fake MI for each electrode, we can get a feature to distinguish the ERD and Fake MI. After that, we were trying to find a channel to classify ERD, but such an electrode did not be found for all electrode because of subjectivity that brain wave signal has. We cannot find an electrode that clearly distinguish. From the reason, we found that Fake MI has subjectivity and does not have a specific area that determine a feature.

Second we were trying to find a reason of Fake MI. When checking an electrode, we didn't find a feature that can classify Fake MI. So for more deep analyze, we were trying to find a reason of Fake MI. If there is a reason of Fake MI, we can classify and distinguish the ERD and Fake MI. In addition to find a cause, we used 128 CH EEG cap that has 128 electrode spot to raise spatial resolution. By using a higher resolution, we can utilize a more and sophisticated electrode area. By verifying ERD pattern, we finally find a cause of Fake MI showing in Fig 16.

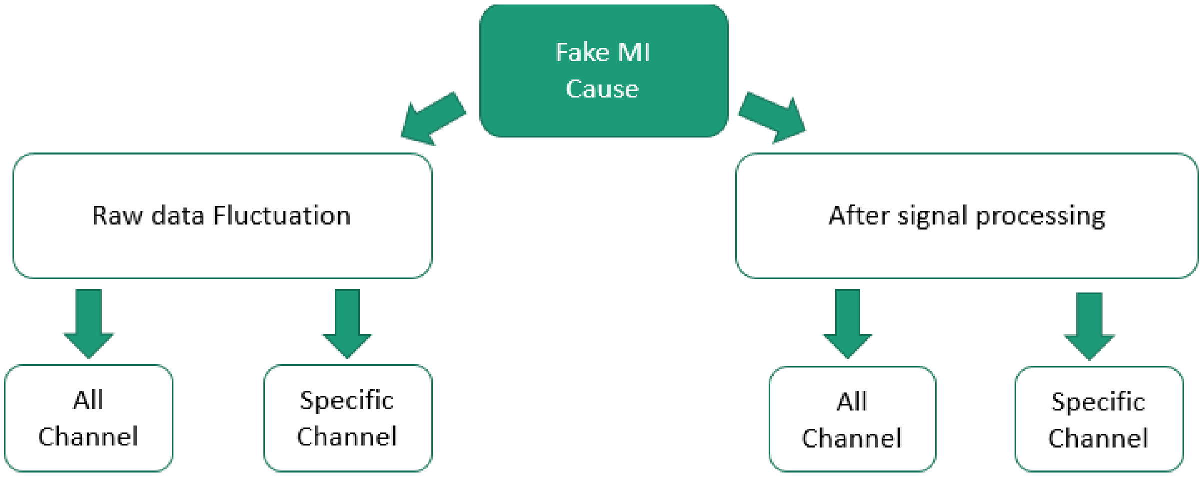

Figure 16. The cause of Fake MI

Fake MI cause can be divided into two class. One is the raw data fluctuation. This reason arise from external noise or artifact. Electrode may be affected by external movement like body movement because EEG electrode is weak to movement noise. So we were set experiment protocol was under the condition that we ask for subject not to move their body or head. However, under the condition, we cannot eliminate noise. The fluctuation can appear in all electrode or specific electrode. The cause of Fake MI by raw data fluctuating is white noise that occur high power spectrum about all frequency range. In order to high power spectrum for all frequency, a specific frequency was also affected by noise. Noise lead to high power amplitude in specific frequency and then high power amplitude dropped at original amplitude. This was similar to ERD pattern and it cause a confusion and appear as Fake MI. When raw data fluctuation appeared, white noise occurred in the frequency graph. Therefore, when white noise appeared, we can eliminate the noise by checking a power spectrum in high frequency range not related to specific frequency range. This method was applied to only region of interest that contains left primary motor area and supplementary motor area. The condition was also applied and performed simultaneously in filtering step. Because region of interest is related to movement that we are interested and if we check the Non-ROI, it is a contradiction to eliminate the Fake MI.

The other is the 'After signal processing'. This cause cannot be found why this performance happen. So we were trying to position the electrode in various site as primary motor area, supplementary motor area and Non-ROI. Using a multi-channel method facilitated ERD and Fake MI classification. If we used this method, we need a channel selection to classify ERD and Fake MI. We assumed that by positioning the electrode in Non-ROI, there is a feature when Fake MI appeared. If when Fake MI occurred at all electrode, Fake MI occurred at the electrode positioned in Non-ROI. To determine the Non-ROI channel, we referred the BRODMANN area. By determining some electrode position that has potential, we tested a possibility of Non-ROI. Fig 17 represent a Non-ROI that was applied in EEG experiment. Table 3 shows the BRODMANN area and the role of that area of selected electrode.

Table 3. BRODMANN area and the role of area of selected electrode

	Brodmann area	**Role of area**
TP8	21	Auditory processing and language
CP6	40	Involved in reading both as regards meaning and phonology
P7 / P8	37	Unknown
T8	22	Right side, melody, pitch and sound intensity

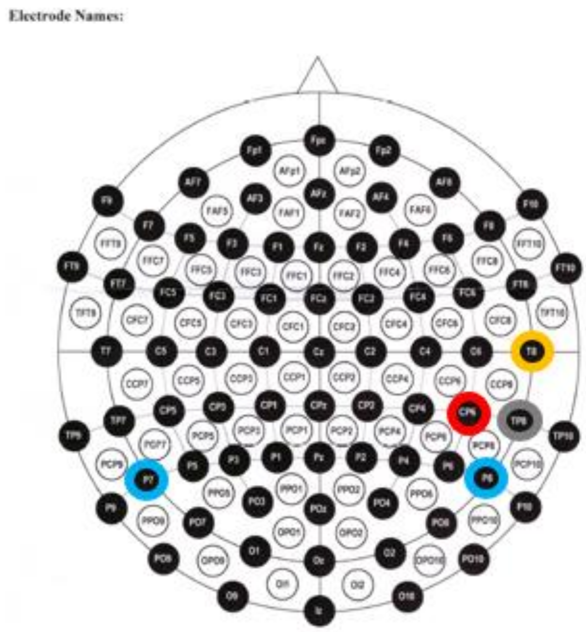

Figure 17. Non-ROI applied in EEG experiment

After selection of electrode, we analyzed the real time data using timeline table that represent the ERD or Fake MI pattern by each electrode as flow of time. Fig 18 show an example of timeline table.

	Timeline	T1(16")	T2(27")	**T3(42")**	T4(57")	T5(1'9")	T6(1'20")	T7(1'28")	T7-f(1'35")	T8(1'40")	T8-f(1'41")	T8-f2(1'46")	T9(1'52")	T9-f(1'56")	T10(2'5")	T11(2'18")
Channel																
SMA(7)		X	O	O	O	X	X	X	O	W	O	W	X	O	O	X
C3(16)		X	O	W	W	X	X	X	X	X	X	W	X	O	O	X
CPC5(13)		X	X	X	X	W	X	X	X	X	X	W	X	W	X	X
CP5(15)		X	X	X	X	X	X	X	X	X	X	W	X	X	X	X
CCP(18)		X	X	X	X	X	X	X	X	X	X	W	X	X	X	X
TP7(12)		O	W	X	X	X	X	X	X	X	X	X	X	X	X	X
C4(25)		X	O	X	O	X	X	X	O	W	W	W	X	O	W	X
CPC6(23)		O	O(delay)	X	P	X	X	X	X	X	W	O	X	O	X	X
CCP6(28)		X	X	X	W	X	X	X	X	W	W	O	X	O	X	X
CP6(21)		X	O	X	P	X	X	X	X	X	W	O	X	O	O	O
TP8(26)		X	O	X	X	X	X	X	X	X	X	X	X	O	O(delay)	O
CP4(29)		X	O(delay)	X	P	X	X	X	X	W	W	W	X	O	X	X
Fz(3)		O	O(delay)	X	P	X	X	X	X	X	O	O	X	O	X	X
FFC1(4)		X	O(delay)	X	P	X	X	X	X	X	W	O	x	O	X	X

Figure 18. Example of timeline table

The horizontal axis represents a time that occurred the ERD or Fake MI. The patterns was verified by operator subjectively so it did not have consistency and discrepancy with machine learning. The perpendicular axis represents a channel to be analyzed. The alphabet 'O' indicated the ERD or Fake MI pattern and 'X' is there is no significant pattern. 'W' shows an ambiguous pattern between 'O' and 'X'. By analyzing multi-channel at the same time, we can verify a feature that can classify the ERD and Fake MI. The feature means a condition of selection of electrode. The feature is different from a meaning of machine learning method. The pattern when ERD and Fake MI occurred appeared differently each specific electrode. We found this phenomenon by verifying the whole pattern of each electrode not only the time of ERD but also the time of Fake MI. Fig 19 shows a condition the ERD and Fake MI.

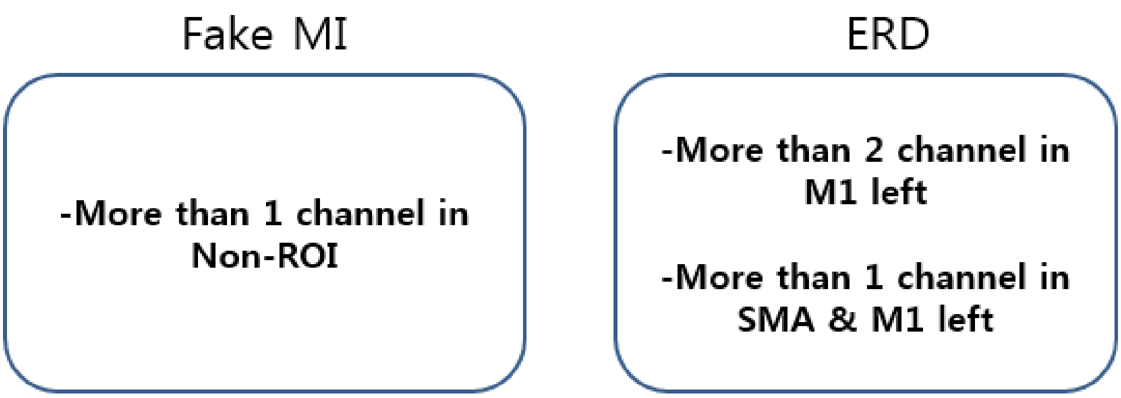

Figure 19. Condition the ERD and Fake MI

The condition of Fake MI is that ERD pattern appear more than 1 channel in Non-ROI area. That condition only occurred when Fake MI appear in specific channel. Whenever Fake MI appeared, ERD pattern may not occur in Non-ROI. However, at least, if ERD pattern was seen more than 1 channel in Non-ROI area, that would be a definite Fake MI. We can verify a role of Non-ROI and classify ERD and Fake MI. The condition of ERD is that ERD pattern appear more than 2 channel in left primary motor area or more than 1 channel in supplementary motor area and left primary motor area. These feature was seen when only true ERD appeared. For all movement trial, ERD condition was not be satisfied. Because experiment condition was that a hand was bound, it was hard to get actual movement feedback.

Finally, we found a reference of classification of ERD and Fake MI. After that, those condition was applied to system. Fig 20 represents a whole system configuration from signal processing to machine learning.

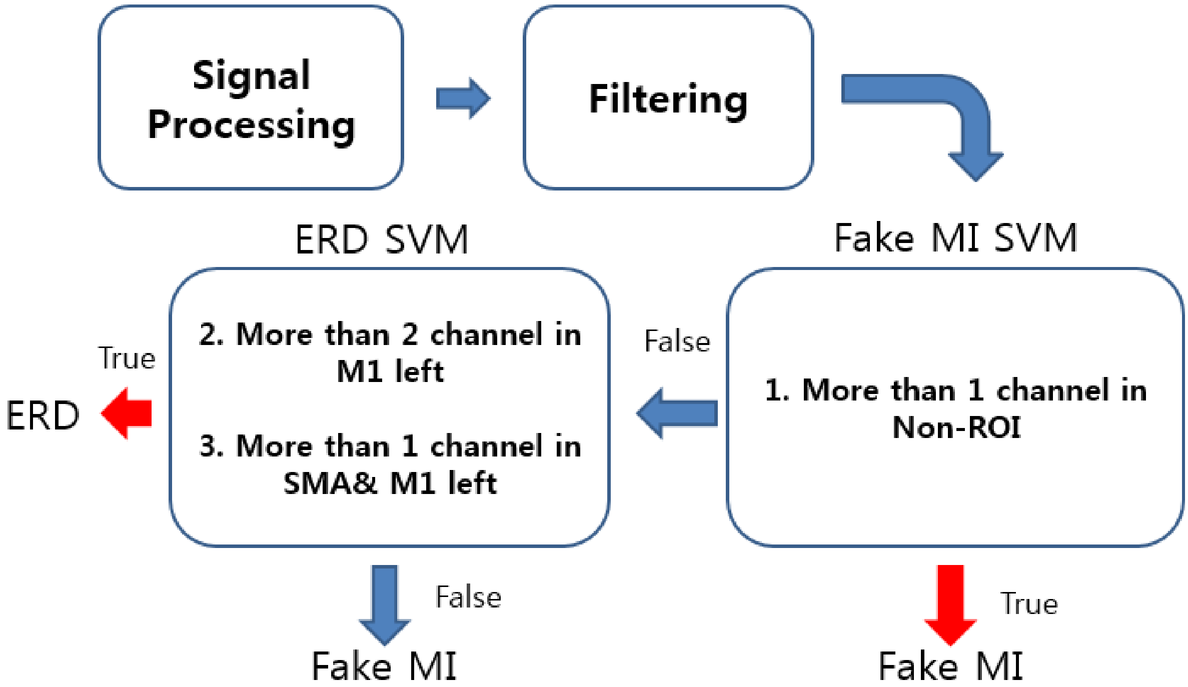

Figure 20. Whole system configuration from signal processing to machine learning

First, signal processing step was performed to data. After that, the data passed filtering step and Machine learning part was executed. According to the condition that we mentioned above, we applied the condition to SVM. If the data was transferred from filtering, Fake MI SVM step was performed to classify and recognize whether the data had ERD pattern in Non-ROI. If Fake MI SVM determined it was true, the data classify as Fake MI. Next, ERD SVM step was executed if Fake MI SVM classify the data as false. Then, ERD SVM condition was applied and if the SVM determine or classify the data was true, ERD SVM classify the data as ERD and 'ERD' expression was printed in command window. This is for interface with robot in further work. If the 'ERD' expression appeared, the signal was sent to robot that connected the system. ERD SVM have two condition and if any condition was satisfied in two conditions, SVM would be executed.

III.Result

3.1 EEG Experiment Result

The result was assessed by SVM accuracy. By executing a real time code combined with SVM algorithm, we can verify the accuracy. In this thesis, accuracy was written as a number of trial not percentage. This was because total number was not fixed in case of Fake MI contrast to ERD. The number of ERD trial was fixed according to protocol. However, Fake MI cannot be estimated when Fake MI appeared. Also this study is about voluntary movement so accuracy is dependent to subject's volition. Therefore, the percentage of accuracy is not important in this thesis.

From timeline table, we selected electrode each subject. Table 4 represents the selected electrode.

Table 4. Selected electrode

	M1 Left	**SMA**	**Non-ROI**
Subject1	CFC5, CCP5, TP7, C3	FCz, FFC1	CP6, TP8, CCP6
Subject2	CFC5, CCP5, TP7, C3	FCz, Cz	C4, CFC6
Subject3	CFC5, CP5, CCP5, C3	FCz, Cz	CFC6, P7
Subject4	CRFC5, CCP5, C3	FCz, Cz	C4, CCP6, CFC6
Subject5	CFC5, CCP5, C3	FCz, Cz	CFC6, P8

These selection shows that there is no big difference of channel location. Although, there is a difference in Non-ROI area, the electrode locations of M1 Left and SMA area are similar each subject. The reason why Non-ROI area is different from each subject is that Fake MI has many kinds of pattern that appear in multi-channel. That is, Fake MI did not have specific channel that ERD pattern appeared from subject to subject. And this point implied that the selection of Non-ROI channel was important. It can affect an accuracy and Fake MI detection.

Next bar graph represents a total ERD trial obtained by analyzing timeline table. (Fig 21) That graph shows an expected result of ERD trial, that is, success trial of each subject and each experiment.

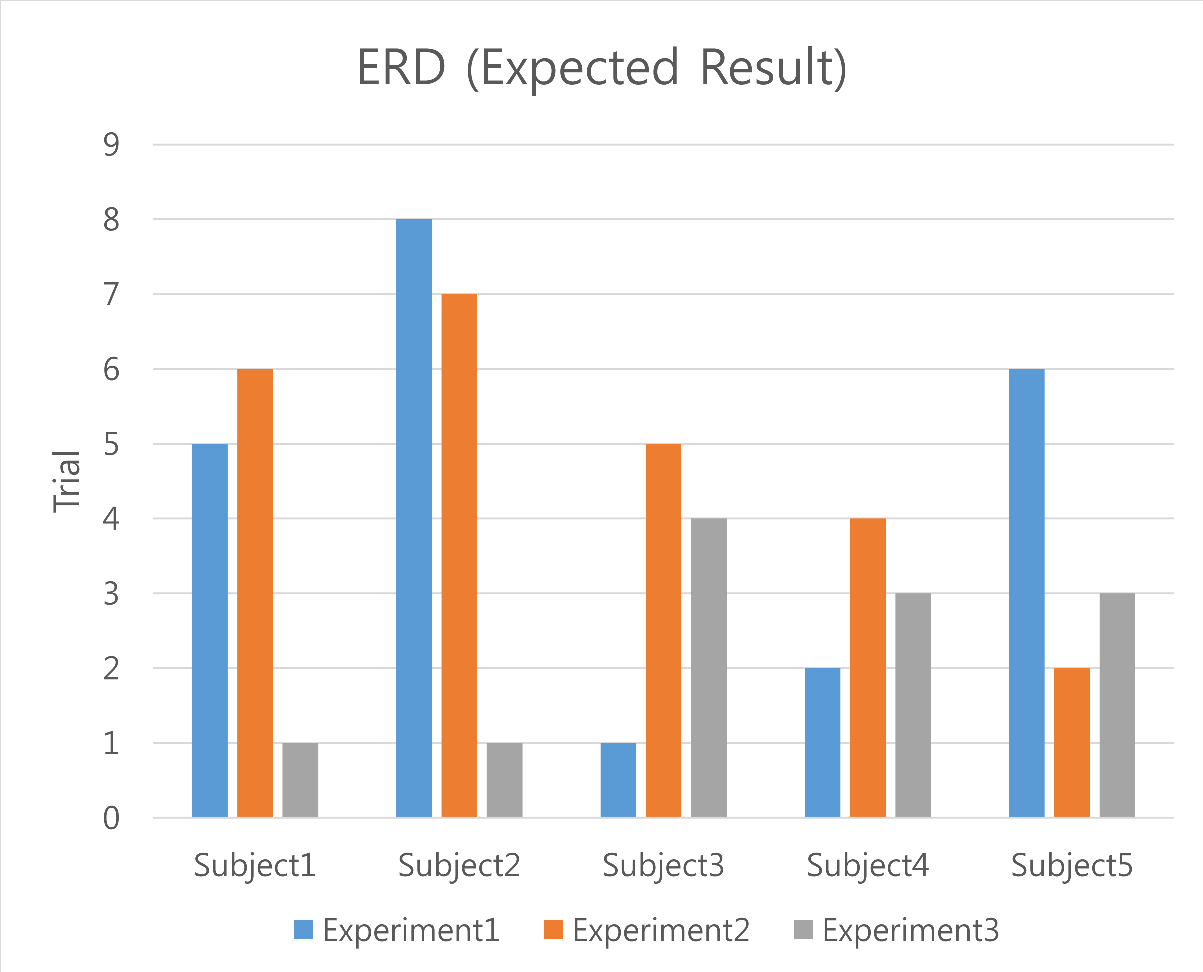

Figure 21. Total ERD trial obtained by analyzing timeline table

Total trial is 30 as we determined protocol in experiment protocol chapter. The result represented low success trial and although there was a difference by subject, mean of success trial were less than one of third of total trial. The reason of this phenomenon was algorithm that eliminating of Fake MI. As we mentioned above, a processed data transferred to machine learning step through filtering step. In machine learning step, first, Fake MI SVM process was performed and if Fake MI SVM determined the data as true, it classify the data as Fake MI. And if not the data transferred to ERD SVM. ERD SVM also classify the data like Fake MI SVM. Most of true ERD classify Fake MI because of Fake MI SVM.

The pattern of ERD occurred in ROI area was distinguished true ERD but in the same time ERD pattern that recognize machine learning occurred in Non-ROI area. So that trial classify as Fake MI not true ERD. This is why success trial is low. These results were determined by operator's decision, so it did not agree with SVM decision.

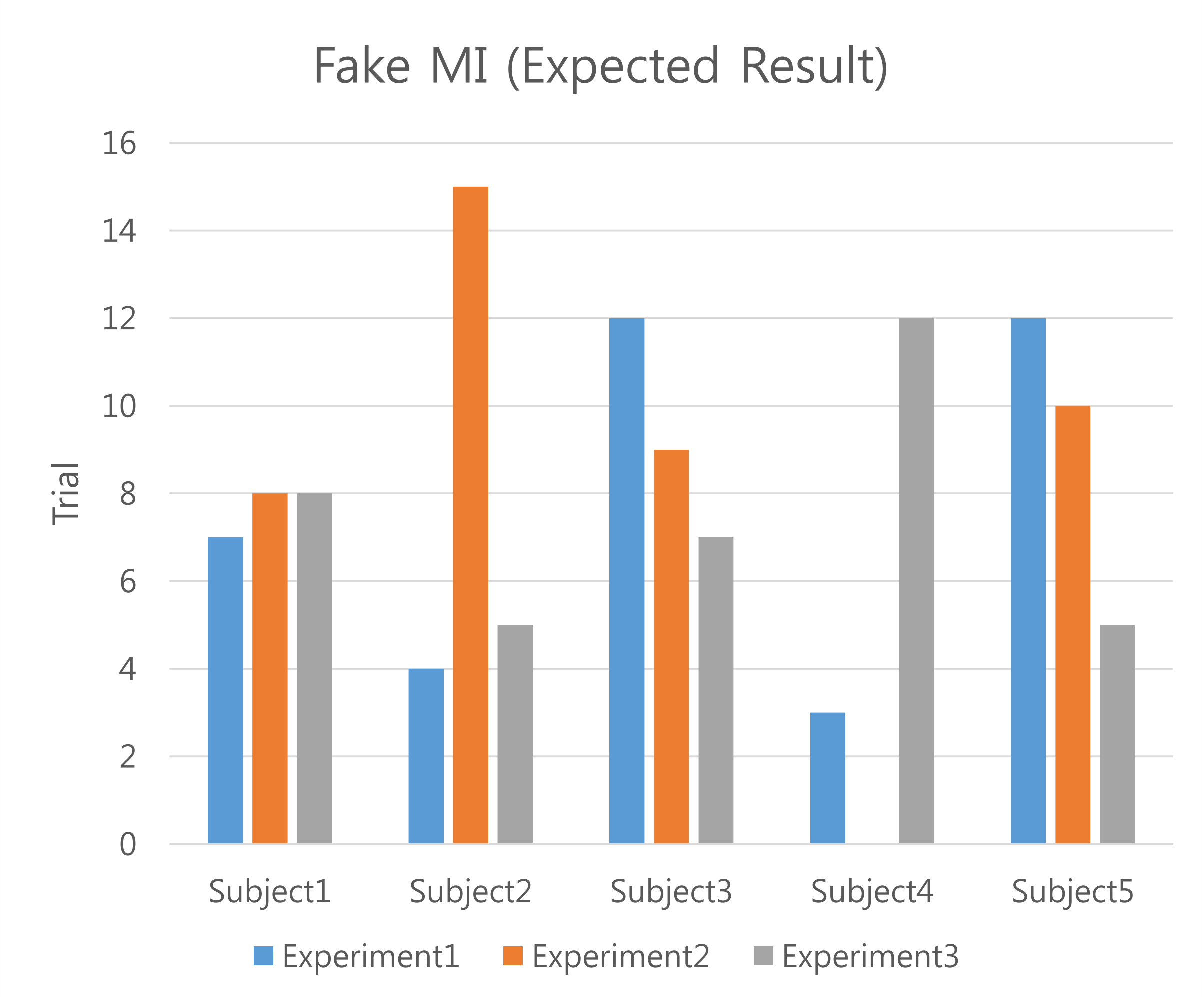

Figure 22. Total Fake MI trial obtained by analyzing timeline table.

These results represented total Fake MI trial showing a total Fake MI trial obtained by analyzing timeline table. (Fig. 22) This graph was also expected result by operator's decision, so it did not agree with SVM decision. As the graph represented, Fake MI trial occurred overall more than success trial. The result (Sub 4, Ex 2) represented that there was no Fake MI trial. This trial would be a drawback of this thesis. We reduced these Fake MI trials by applying algorithm and next SVM result would be represented.

3.2 Machine learning Result

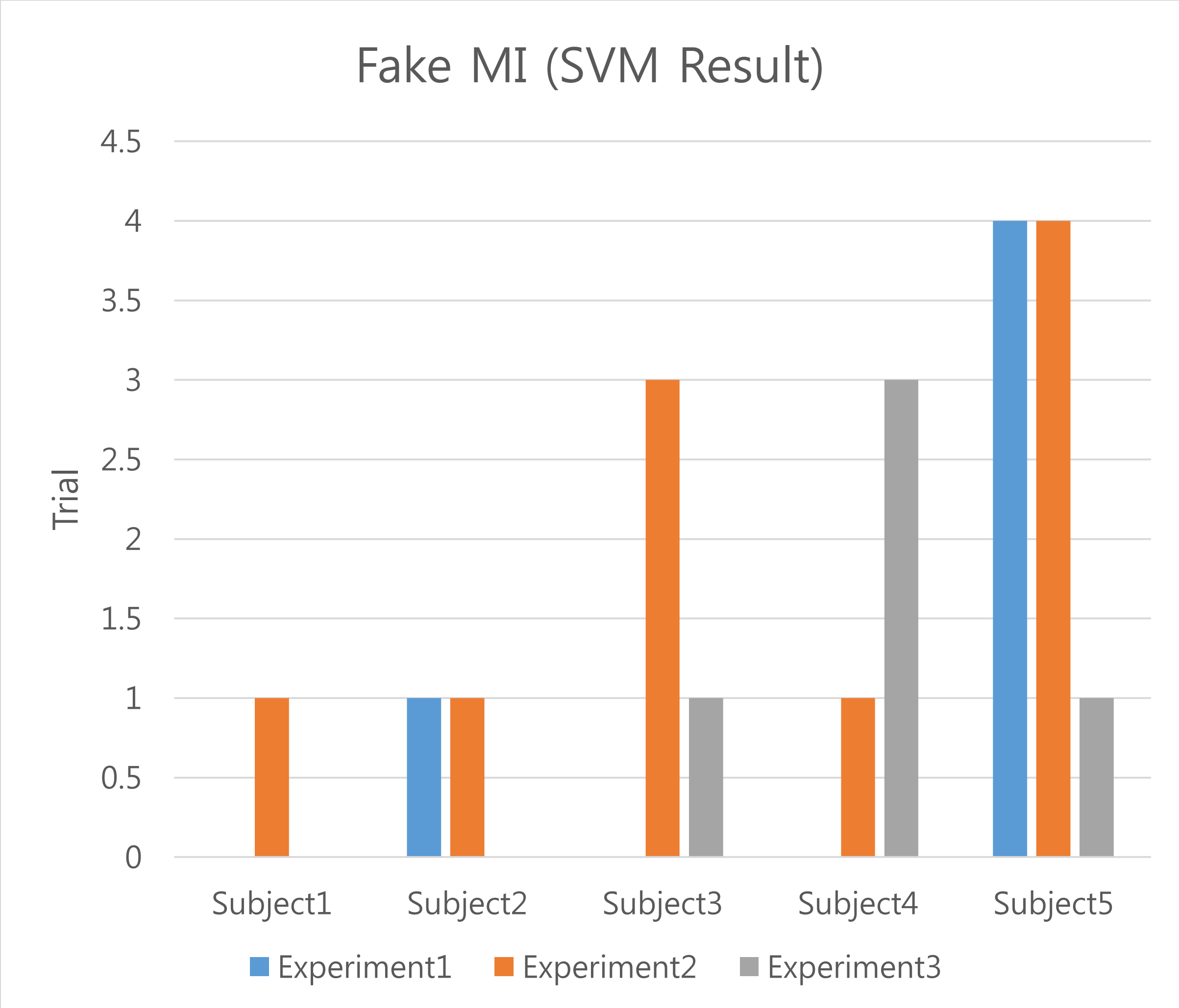

Figure 23. Fake MI trial applying SVM and algorithm

These graph (Fig 23) represented Fake MI trial that apply SVM and algorithm. Most of experiments represent zero or one false detection. This graph shows that algorithm and SVM worked well and efficiently. There values showed trials of false detection. It means that these trials classify as ERD by SVM but actually it is Fake MI. Subject 5 was difficult to determine a training data. By adjusting the training data of SVM, the result can be different. However, adjusting a training data is difficult because of subjectivity of ERD. We find an optimal training data to reduce Fake MI trial.

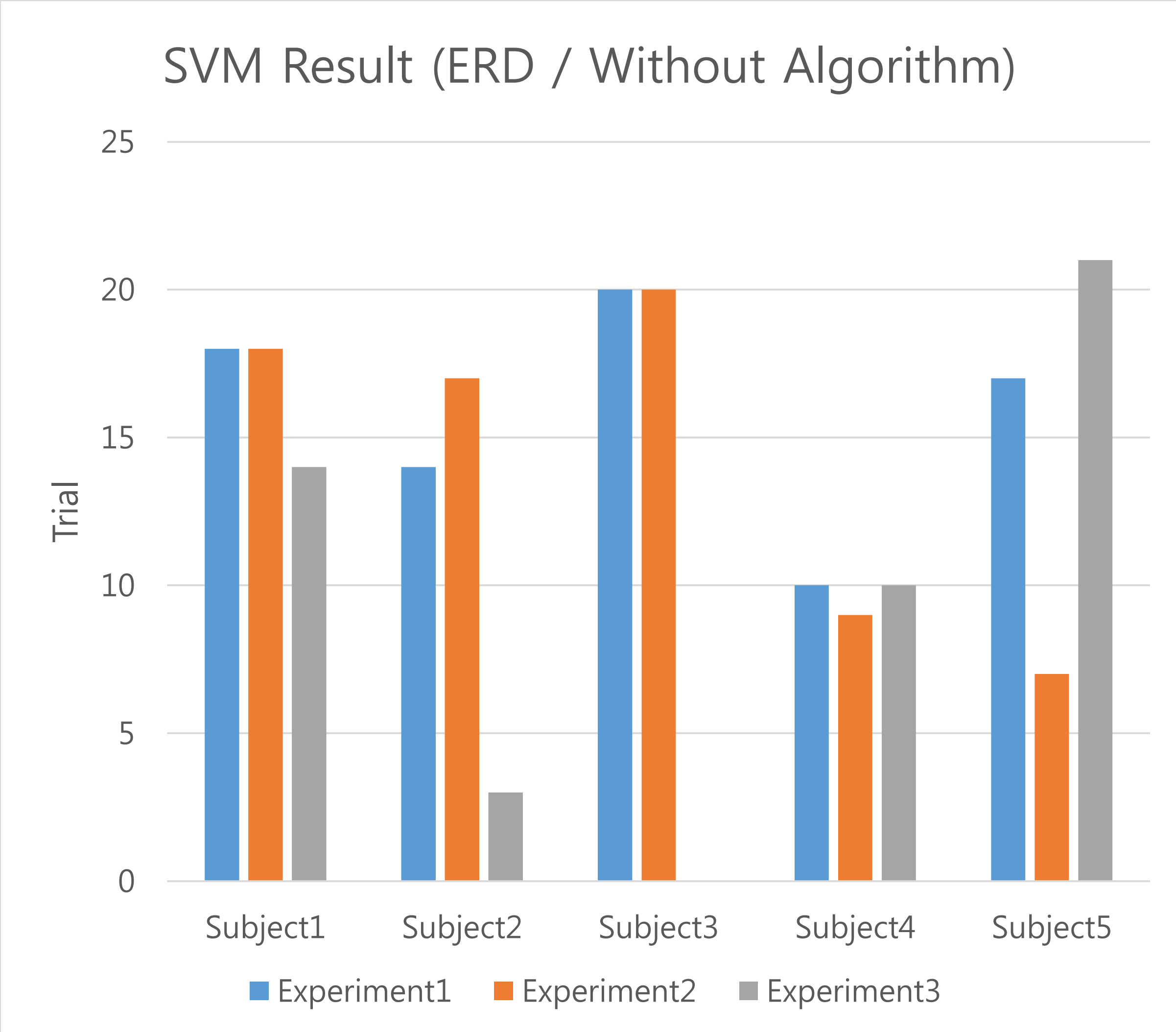

Figure 24. SVM result of ERD trial that did not apply algorithm

These graph (Fig. 24) represented SVM result of ERD trial that did not apply algorithm. Without algorithm, a total trial of ERD can be increased. But without algorithm, Fake MI had more impact on this result. Most of subjects appear more success trial than with algorithm. Experiment 3 in subject 3 trials were not applicability. Because there were so many trials in EEG data. We cannot count an exact number of trials. Next graph (Fig. 25) shows SVM result of Fake MI trial that did not apply algorithm.

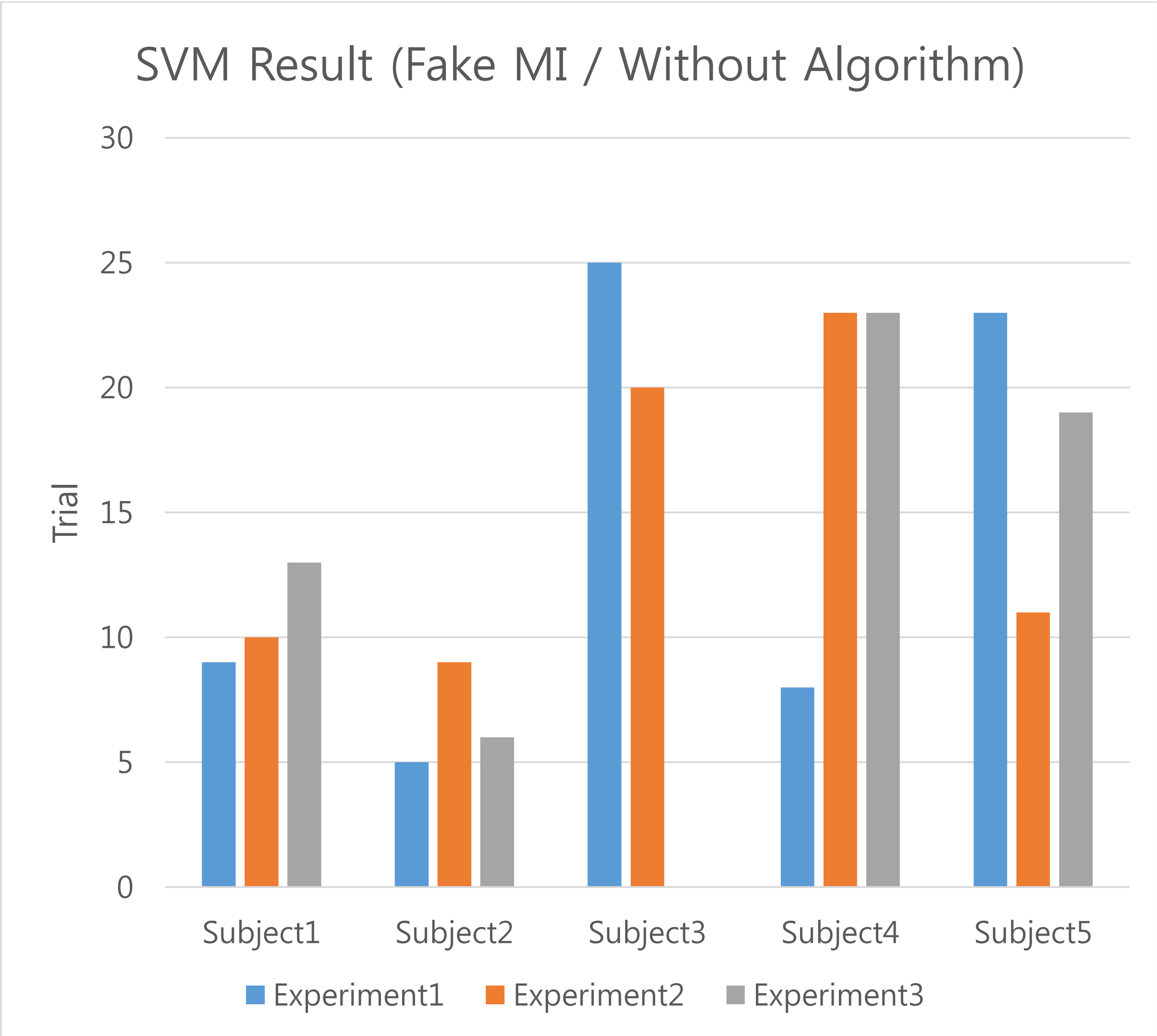

Figure 25. SVM result of Fake MI trial that did not apply algorithm

As the graph represented, many trials appeared during experiment. The graph shows that it has a possibility that a number of Fake MI appeared if algorithm did not exist. That graph represented an importance of eliminating of Fake MI. Alike SVM result of ERD without algorithm, the number of trials in experiment3 in subject3 were not applicability. Because there were so many trials in EEG data.

IV. Discussion

This thesis is subject-specific real time motor imagery detection scheme for robot-aided hand rehabilitation. The result of SVM represents the success trial of ERD and false detection of Fake MI. From the result, we have successfully demonstrated that Fake MI detection can be reduced and can build the real time system as specific-subjects for detecting intention of human voluntary movement. To realize those purpose, first, we built a system that detect a voluntary movement. To realize the system, we made a protocol without external cue and apply algorithm that eliminate Fake MI. As a result, we can reduce Fake MI trial. Second, the system was adopted to each subject. For that, specific parameter was applied to each subject's code with each ERD pattern for training data of support vector machine.

However, the whole system could not eliminate Fake MI completely. The reason cannot be found yet. We only assumed that the reason was voluntary movement and machine learning. This thesis was based on voluntary movement, subject's volitional action, so much portion were assigned to subject in experiment protocol and in other words, there were small portion that operator could control. Or unconscious intention of movement appeared during experiment because there were no external cue that control subject's conscious, imaginary or intended movement. Next is a performance of machine learning. Machine learning is based on a modeling that generated by computer algorithm and has quantitative value. It divide a data into two classification in this system. However, machine learning can misclassify the data contrast to true classification. It may be generated by vague pattern which is hard to distinguish as true or false because of subjectivity that brain wave signal has. Moreover, to eliminating Fake MI aroused the true ERD elimination. The algorithm that remove Fake MI also eliminate the ERD and that cause low success trials. Low success trial has another reason because experiment protocol has constraint movement but it has a small part of the reason. Fake MI reduction and success trial of ERD are complementary relationship. As long as Fake MI reduction is up, the success trial of ERD is down and as long as success trial of ERD is up, Fake MI reduction

Another limitation is overlapping executing of the real time code. Now the code consist of function that execute 100 Hz. If filtering process was performed continuously, the signal processed data in that time was also transferred to machine learning process continuously as the function code sampling time. It causes a burden to system and phenomenon of overflow of data occurred. Overflow of data is that transferred data is stagnant because of some reason such as other processing step like support vector machine. This overflow phenomenon occurred problem because it causes characteristic of real time data transferring. If phenomenon of overflow continue, transferred data from EEG was omitted from Vision software and it is a problem in consisting of real time system.

Determining of the time of ERD are also important. To construct the real time system, it is important to send a signal to interfaced robot so the time to send a signal is important to make a voluntary-like movement. However, ERD did not occur at a particular time so it is hard to send a signal at a fixed time. This point should get solved to connect with rehabilitation robot. To determine a specific frequency band is also important in this study. We assume that ERSP graph represents well frequency band that we are looking for. However, the result of ERSP graph and specific frequency band of subject sometimes have discrepancy. We do not know exact reason but it is guessed that ERSP graph show statistics results so it may not be matched with single trial result. Machine learning method should be adjusted for better performance. The result of SVM can be improved by training data so it is significant point that what data will be trained for support vector machine. Experiment protocol is modified for future research. Now we set experiment protocol with bound hand with strap but this is just for making a similar circumstance of patient. It is not exactly matched with patient's conditions and EEG data of patient is different from healthy subject so we need to make a protocol that help detection of ERD pattern and reduce Fake MI trial for patient.

V. Conclusion

This study is subject-specific real time motor imagery detection scheme for robot-aided hand rehabilitation. We built the real time system that be able to perform voluntary-like movement. During building the system, we have found problems like Fake MI. Fake MI is the factor that interrupt a correct rehabilitation therapy. So we concentrated on classification ERD and Fake MI and elimination Fake MI. The result represented that the algorithm applied to this system can almost eliminate Fake MI. However, during the step, we also lost true ERD that we want to detect. This is the reason why ERD trial is lower than total trial. If we wanted to increase success trial, we cannot avoid increase of false detection. Also we make the real time system that suitable to each subject. By applying specific frequency and channel that used to analyze, we can make a suitable code for each subject to improve applicability. In addition to specific frequency and channel selection, ERD pattern for SVM is used to match subjectivity.

From the contribution for this thesis, we can detect intention of human's movement by eliminating wrong detection, subject-specific parameter, reducing electrode used. Some subject has low success trial because of algorithm to eliminate Fake MI. However, eliminating Fake MI is more important than improve success trial because wrong detection has a large impact on subject's motor learning so subjects cannot restore their motor function. Also success trial is relied on the subject's volition because it is voluntary movement. If subject has a will to move their hands, success trial will be improved with correct rehabilitation therapy and this system will help them.

Appendix

1. Introduction

This chapter was for new experiment. Until now, we performed experiment about imaginary movement, however, the protocol was not clear because of aspects of motor imagery. Previous experiment condition was constraint movement with strap so movement was not appear outside but activation of muscle was performed by subject. There was some controversy about constraint movement. Because actual movement existed by muscle’s activation but there was no feedback caused by outside movement. So it was not clear whether this experiment protocol is motor imagery or actual movement. Therefore, the protocol was changed to clear a paradigm that include an actual movement. EEG electrode position was also changed by referring to previous study. [1, 25-27] New protocol was based on actual movement so relocation of electrode position was performed. The purpose of new protocol is to verify applicability of algorithm that proposed in this study through new protocol. So under the new experiment, it can be proved whether the proposed algorithm was worked well or not. If it was proved, also, clear motor imagery protocol could be applicate for patient.

2. Method

2.1 Electrode position

Relocation of electrode position was referred by previous study. [1, 25-27] In [1], task was wrist extension and use 27 electrodes. (F3, F7, C3A,C1, C3, C5, T3, C3P, P3, T5, F4, F8, C4A, C2, C4, C6, T4, C4P, P4, T6,FPZ, FZ, FCZ, CZ, CZP, PZ and OZ) Fig 26 represents 10-20 International system electrode position.

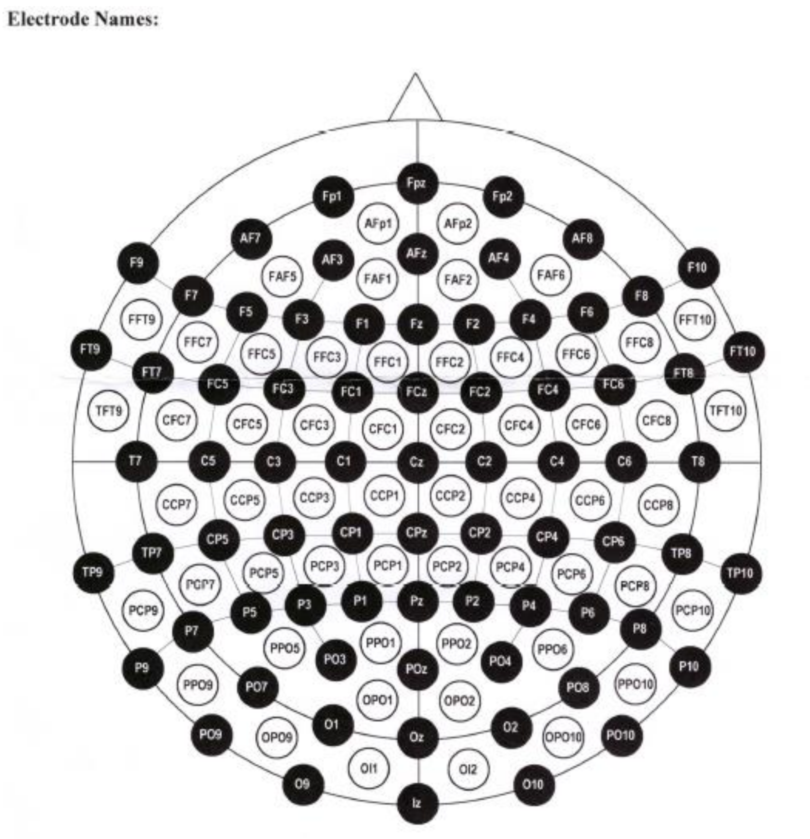

Figure 26 10-20 International system electrode position (128 CH)

Also, feature extraction called Bhattacharyya Distance of the study was used for C1, C3, C3P. Those channel were activities with better result than other spatial location.

In [25], experiment task was left and right hand movement, opening and closing the fist. The study included hand movement and used 64 channel. They referred that neural activity correlated to the executed left and right hand movements is almost exclusively contained within the channels C3, C4 and CZ. [25, 26] Other task of previous study was hand squeeze. [27] In the study, they used 29 channels. Based on those studies, we relocated electrode position. Fig 27 shows a new electrode position. By referring previous study, we included an electrode location that used in those studies.

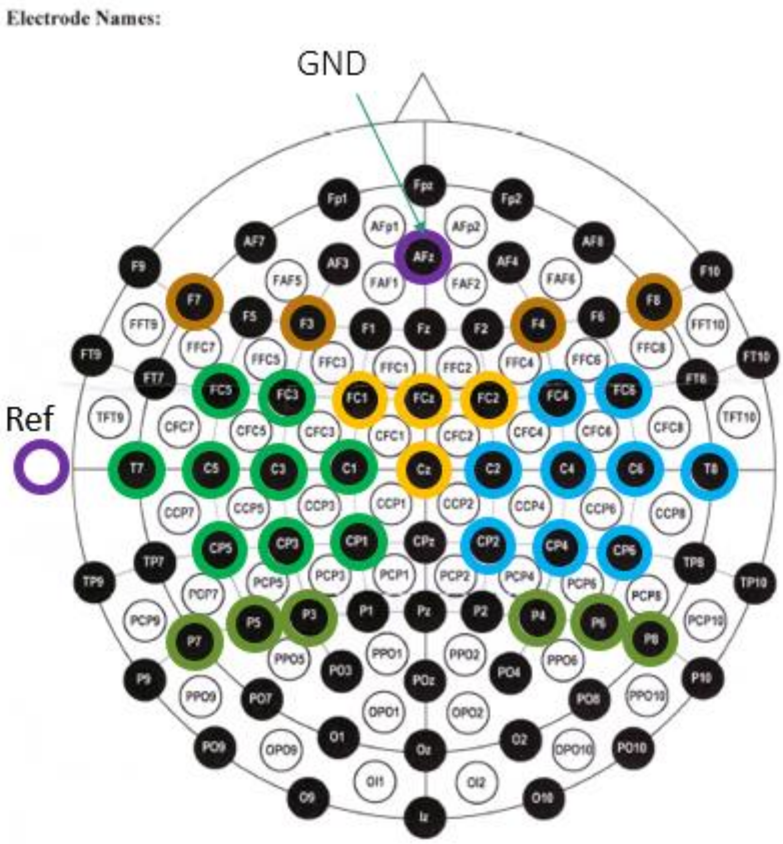

Figure 27. Electrode position

2.2 Experiment protocol

Experiment protocol was changed for actual movement. One healthy subject participated the experiment. (Subject 1)

1) EEG cap was put on subject's head according to 10-20 International System

2) The 32 electrodes were placed on the scalp sites of the subject.

3) The subject tried to perform a hand extension whenever subject want

4) Total 30th trial was performed by subject. There was no fixed time between trials

2.3 ERD / Fake ERD Classification

The protocol was for actual movement so in this condition Fake MI should be changed the name as Fake ERD. The definition of Fake ERD is a false ERD pattern that occur during rest time. It is not related to movement but its pattern is similar to ERD so SVM can be confused by them. Fake ERD also has same definition but the experiment protocol was changed so the name also should be changed. Fake ERD appeared during rest time. The duration of rest time is a time excluding from 4 seconds before movement onset to 2 seconds after movement onset. (Figure 28) Range to extract Fake ERD is selected channel for ERD, that is, ROI area. Non-ROI area was not considered to define Fake ERD. The algorithm to classify ERD and Fake ERD was applied as same method. However, condition was added in ERD SVM.

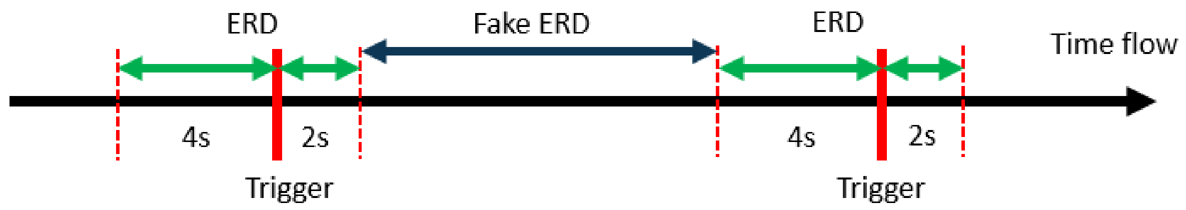

Figure 28. Duration of ERD and Fake ERD

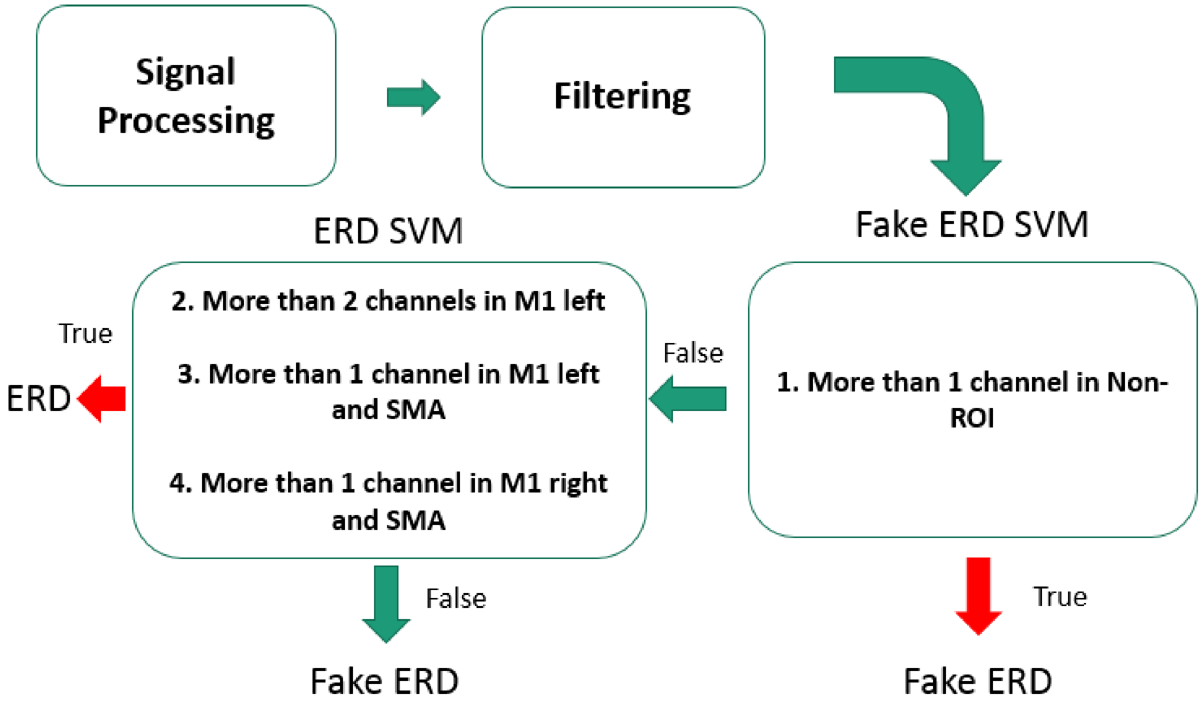

Figure 29. Whole system configuration from signal processing to machine learning

The reason why ERD SVM condition was changed is that location pattern of electrode for ERD is different from previous experiment. This experiment was based on actual movement so brain activation is not same as previous one. By analyzing timeline table, we found a pattern of electrode location when movement onset was occurred. Unlike original protocol, the new protocol with actual movement had different electrode location that ERD appeared. In this protocol, we did not consider Non-ROI area. The electrode position already covered the area according to BRODMANN area. Analyzing timeline table was a method that find a channel of Non-ROI and ROI. Although condition was added and not same as previous one, overall system configuration was not changed. Based on above system, electrode selection and result would be represented next chapter.

3. Result

The result was assessed by SVM accuracy same as previous result. First, we selected channel of ROI and Non-ROI through analyzing timetable. (Table 5)

Table 5. Selected electrode

Subject1	Channel 1	Channel 2	Channel 3
M1 Left	C1, C3, CP3, CP5	C1, C3, CP3, CP5	C1, C3, CP3, CP5
M1 Right	C4, C6	C4, C6	C4, C6
SMA	FCz, FC2, Cz	FCz, FC2, Cz	FCz, FC2, Cz
Non-ROI	CP2, CP6	T7, P7	T8, P7

M1 left and right, SMA is ROI of the subject. To find a channel of Non-ROI, we applied different Non-ROI channel. To find a channel of NOI, we selected a channel that the number of ERD were many when movement onset occurred. Table 6 represented the number of trial of ERD in ROI channel.

Table 6. Number of trial of ERD in ROI

Channel	FCz	FC2	Cz	C1	C3	CP3	CP5	C4	C6
No.	10	13	8	8	5	4	4	7	7

It is not only point that the number of ERD trial determine a channel of ROI. Channels that can classify ERD and Fake ERD and the number of trial of ERD were element that determine the channel of ROI. Also, we analyze a number of Fake ERD. The duration of Fake ERD was represented in Figure 28. And we also determine a reference channel that define Fake ERD. Because the number of trial of Fake ERD could be different as selection of channel.

Table 7. Number of trial of Fake ERD according to selected channel

Selected Channel	No. of trial
C3,Cz,C4	7
C1, C3, CP3, CP5, C4, C6, FCz, FC2, Cz	9
FC1,FC2,FCz,T7,C5,C3,C1,Cz,C2,C4,C6 T8, CP5,CP3,CP1,CP2,CP4,CP6,P7,P5,P3 P4,P6,P8	13

Table 7 shows the number of trial of Fake ERD according to selected channel. The more selected channel, the number of trial of Fake ERD increase. To detect ERD, we focused on channel in ROI area. That signified Fake ERD was also related to ROI area, that is, Fake ERD means that a false ERD pattern that occur during rest time and it can be confused with ERD. So Fake ERD was occurred in ROI area and the reference channel should be in ROI area. Those results are estimated value and were not applied SVM method. Final result is as in the following.

Table 8. SVM Result

Subject1	No. of trial(ERD)	No. of trial(Fake ERD)
Channel 1	0	0
Channel 2	5	0
Channel 3	3	0

Table 8 represented SVM result of number of trial of ERD and Fake ERD. The number of trial is low than one fourth of total trial. This is because of proposed process to eliminate Fake ERD. So the number of Fake ERD is zero. Also, according to the channels of Non-ROI, the number of trial of ERD can be different. It is important to select Non-ROI channel that can distinguish ERD and Fake ERD. Table 9 shows SVM result without proposed process, that is, there is no Fake ERD SVM process.

Table 9. SVM Result without proposed process

Subject1	No. of trial(ERD)	No. of trial(Fake ERD)
ROI Channel	16	5

If we did not apply process that eliminate Fake ERD, it was occurred on between trials contrast to movement intention of subject. So to avoid such a false motor learning, we need to apply process to eliminate Fake ERD. The number of trial of ERD shows similar result to previous study [1]. In [1], they only count the number of trial of ERD and number of trial is between 33% and 47%. They represented a result of prediction of human intention of movement but paradigm is similar to this study so the study [1] can be a proper reference paper to compare the result.

4. Conclusion

This appendix is to verify applicability of algorithm that proposed in this study through new protocol. The result of SVM represents the success trial of ERD and false detection of Fake ERD same as previous experiment. From the result, we have successfully demonstrated that Fake ERD detection can be eliminated and can build the real time system as specific-subjects for detecting intention of human voluntary movement.

However, the success trial of ERD is low compare to previous result although new experiment was performed only one. The reason cannot be found yet. More experiment should be performed to prove that but ERD is depend on subject's volitional movement. So it cannot give a guarantee that more experiment would show more success trial of ERD. Only thing that can know from data analysis is that it is more difficult to distinguish between ERD and Fake ERD. The locations that occurred ERD is similar with Fake ERD so the location pattern has no feature that classify ERD. Selecting Non-ROI channel has many number of case. Among them, we showed representative case. Like this, finding Non-ROI channel to classify ERD and Fake ERD is difficult. Moreover, to eliminating Fake ERD aroused the true ERD elimination. The algorithm that remove Fake ERD also eliminate the ERD and that cause low success trials.

The conclusion is that to eliminate Fake ERD is difficult and should find another method to classify Fake ERD. The proposed process was also worked to eliminate Fake ERD but efficacy was decreased for realization of voluntary movement. Therefore, to realize the voluntary system we researched more improved algorithm that enhance efficacy of ERD or should find other simple method.

Reference

[1] Ou Bai , Varun Rathi , Peter Lin , Dandan Huang , Harsha Battapady , Ding-Yu Fei , Logan Schneider , Elise Houdayer , Xuedong Chen , Mark Hallett. Prediction of human voluntary movement before it occurs. *Clinical Neurophysiology*. Vol 122. 2012. 364-372.

[2] Kornhuber HH, Andrews HL. Electro-encephalography. Ⅲ. Normal differentiation of occipital and precentral regions in man. *Arch Neurol Psychiatry*. Vol 284. 1965. 95-115.

[3] Pfurtscheller G. Central beta rhythm during sensorimotor activities in man. *Electroencephalogram Clinincal Neurophtsiology.* Vol 51. 1981. 253-264.

[4] Kai KA, Cuntai G, Karen Sui GC, Beng Ti A, et al. A Large clinical study on the ability of stroke patients to use an EEG-based motor imagery brain computer interface. *Clinical EEG and Neuroscience*. 2011;42;4 253-258.

[5] K. Nagai, Y. hayashi, K. Ito, R.C.V. Loureiro, S.J. Nasuto and W.S. Harwin. Proposal of a Floating Mechanism Based on magnetic Levitation method toward EEG driven robotic system. *Proceedings of Robotics Symposia*. 2013.

[6] K. Kawahira, M. Shimodozono. Rehablitation to promote the relearning movement and paralysis recovery for stroke patients. *IEEE International Conference on Society of Biomechanisms Japan (SOBIM*). Vol 31. 2007. 201-205.

[7] Porter R, Lemon R. Corticosptnal function & voluntary movement. Oxford: Clarendon Press; 1993.

[8] Wilson F. The hand: how its use shapes the brain, language, and human culture. *New York: Pantheon*; 1998

[9] Wing A, Haggard P, Flanagan J, Hand and Brain:the neurophysiology and psychology of hand movements. New York: *Academic Press*; 1998.

[10] Connolly K. The psychobiology of the hand. London: *MacKeith Press*; 1999.

[11] Mountcastle V. The sensory hand: neural mechanisms of somatic sensation, Boston, MA: *Harvard University Press*; 2005.

[12] Baron J, Cohen L, Cramer S, Dokin B, Johansen-Berg H, Loubinoux I, et al. Neuromiaging in stroke recovery: a position paper from the first international workshop on neuroimaging and stroke recovery. *Cerebrovasc Dis* 2004; 18: 260-7.

[13] Luft A, McCombe-Waller S, Whitall J, Forrester L, Macko R, Sorkin J, et al. Repetitive bilateral arm training and motor cortex activation in chronic stroke: a randomized controlled tiral. *JAMA* 2004; 292; 1853-61.

[14] Nudo RJ. Postinfarct cortical plasticity and behavioral recovery. *Stroke* 2007; 38: 840-5.

[15] Mahnaz A,Cuntai G, Kai Keng A, Chai Quek. Optimizing the Channel Selection and Classifcation Accuracy in EEG-Based BCI. *IEEE TRANSACTIONS ON BIOMEDICAL EGNINEERING*, VOL. 58, NO.6, JUNE 2011.

[16] Dennis J. M, A Todd L, Jonathan R.W. Design and operation of and EEG-based Brain-computer interface with digital signal processing technology. *Behavior Research Methods, Insturments & Computers* 1997. 29(3), 337-345.

[17] Pfurscheller G, Lopes da Silva FH. Event-related EEG/MEG synchronization and desynchronization: basic principles. *Clinical Neurophysiology* 1999;110: 1824-1857.

[18] Pfurscheller G, Neuper C, Flotzinger D, Prehenzer M. EEG-based discrimination between imagination of right and left hand movement. *Electroenceph Clin Neurophysiol* 1997;103: 642-651.

[19] C. Guger, H. Ramoser, G Pfurtscheller. Real-Time EEG analysis with subject-specific spatial patterns for a brain-computer interface. *IEEE TRANSACTIONS ON REHABILITATION ENGINEERING*, VOL.8, NO.4 , 2000.

[20] Yijun Wang, Yu-Te Wang, Tzyy-Ping Jung. Translation of EEG spatial filters from resting to motor imagery using independent component analysis. *PLOS ONE*. Vol 7. Issue 5. May 2012.

[21] Kai Keng A, Karen Sui G.C, Kok Soon P, Chuamchu Wang, et al. A Randimized Contrilled Trial of EEG-based motor imagery Brain-computer interface robotic rehabilitation for stroke. *Clinical EEG and Neuroscience*. 2014.

[22]Girijesh Prasad , Pawel Herman , Damien Coyle , Suzanne McDonough , Jacqueline Crosbie. Applying a brain computer interface to support motor imagery practice in people with stroke for upper limb recovery : a feasibility study. *Journal of NeuroEngineering and Rehabilitation*. 2010.

[23] Chang, C. C., & Lin, C. J. (2011). LIBSVM: a library for support vector machines. ACM Transactions on Intelligent Systems and Technology (TIST), 2(3), 27.

[24] Paul Otten. Automating the Fugl-Meyer Assessment with Supervised Machine Learning. DGIST. 2015.

[25] Mohammad H. Alomari, Aya Samaha, Khaled AlKamha. Automated Classification of L/R Hand movement EEG Signals using Adcanced Feature Extraction and Machine learning. *Int J of Adcanced Computer science and Applications* Vol 4. No 6. 2013.

[26] Jason Sleight, Preeti Pillai, Shiwali Mohan. Classification of Executed and Imagined motor movement EEG signals. *Computer Science and Engineering , University of Michigan*. 2009.

[27] Valerie Morash, Ou Bai, Stephen Furlani, Peter Lin, Mark Hallett. Classifying EEG signals preceding right hand, left hand, tongue, and right foot movements and motor imageries. *Clinical Neurophysiology* 119(2008) 2570-2578.

요 약 문

로봇을 이용한 손 재활치료를 위한 피험자 맞춤형 실시간 움직임 의도 파악 방법

본 논문은 재활을 위한 움직임 의도 파악을 다룬다. 최근에 뇌파 측정 장치에 기초로 하여 상상에 의한 움직임을 감지하는 방법이 로봇을 이용한 재활 치료의 효과 증가를 위해 적용되고 있다. 목표는 자연스러운 움직임을 만들 수 있고 피험자 맞춤형 재활치료가 가능한 맞춤형 실시간 시스템을 실현화 하는 코드를 구현하고 사건관련 비동기화 와 잘못된 움직임 의도가 구분 가능한 실시간으로 시스템을 수행할 수 있는 간단한 방법을 개발하는 것이다. 뇌파측정 장치로는 뇌전도 장비를 이용하며 실시간 신호처리를 위해 매틀랩 프로그램을 이용한다. 사건 관련 비동기화는 사람의 움직임의 의도가 나타날 때 특정 주파수 영역에서 발생한다. 이 논문에서는 우리는 사건 관련 비동기화를 감지하기 위해 기계학습이라는 방법을 사용한다. 그 알고리즘으로 서포트 벡터 머신이라는 방법을 이용한다. 서포트 벡터 머신의 결과는 낮은 성공 횟수와 낮은 잘못된 의도 판단 횟수로 나타난다. 잘못된 의도 파악을 제거하기 위한 알고리즘이 또한 사건 관련 비동기화 성공 횟수를 줄여주는 역할을 한다. 자발적인 움직임을 수행할 수 있는 실시간 시스템을 만들었다. 그 시스템을 구축하는 동안 잘못된 움직임 의도라는 문제점을 발견하였다. 그것은 올바른 재활 치료를 방해하는 요소가 된다.

핵심어: 움직임 의도, 인간의 의도, 자발적인 움직임, 사건관련 비동기화, 뇌전도, 서포트 벡터 머신, 기계학습, 실시간 신호처리