Master's Thesis
석사 학위논문

Development of Rehabilitation Applications by Using Wearable Sensors

Sanghoon Jeon(전 상 훈 全 商 勳)

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Advisor: Professor Sang Hyuk Son

Advisor: Professor Taejoon Park

Co-Advisor: Professor Il Kon Kim

by

Sanghoon Jeon

Department of Information and Communication Engineering

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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 Information and Communication Engineering. The study was conducted in accordance with Code of Research Ethics[1]

. . 2013

Approved by

Professor Sang Hyuk Son (Signature)
(Advisor)
Professor Taejoon Park (Signature)
(Advisor)
Professor Il Kon Kim (Signature)
(Co-Advisor)

[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.

Development of Rehabilitation Applications by Using Wearable Sensors

Sanghoon Jeon

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

. . 2013

Head of Committee ________________(인)

Prof. Sang Hyuk Son

Committee Member _________________(인)

Prof. Taejoon Park

Committee Member _________________(인)

Prof. Il Kon Kim

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ABSTRACT

As aging population becomes a major issue in a number of countries, more medical services are increased. Wearable sensor will substitute for the role of healthcare providers to accommodate increasing requirements of rehabilitation which has characteristics of labor-intensive and time-consuming. We chose two wearable sensors such as 6 degree of freedom inertial measurement unit (6-DOF IMU) and surface electromyography (SEMG) sensor, and proposed rehabilitation applications related to early detection of disorders and home rehabilitation. First, we proposed a novel system for monitoring in-sleep stroke by detecting abnormal activity ratio of the left and right arms from wearable the 6-DOF IMU sensor which consists of an accelerometer and gyroscope sensor. We extracted multiple features for distinguishing between normal people and stroke patients with hemiparesis from the sensor data, and detected stroke by sliding window method with stroke thresholds according to the each feature. The system discriminated stroke 75.48% by the accelerometer sensor and 97.12% by the gyroscope sensor in sleep data of the stroke patients with hemiparesis. Second, we tested a feasibility of the SEMG pattern recognition for training of activity daily life. We experimented from simple motions to complicated motions considering variables such as time, electrode position and person change. The results showed that the SEMG pattern recognition is largely influenced by the three variables because of structural problems in the muscle and the SEMG sensor. We concluded that the SEMG is appropriate in simple application such as co-contraction EMG detecting whether a muscle is activated.

Keywords: Rehabilitation applications, in-sleep stroke, SEMG pattern recognition, co-contraction EMG

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I. Introduction

Our body has a self-renewing and healing ability. To maintain an appropriate and good condition is very important in curing a disease. When our face is wounded, the wound will be completely healed by the proper cure such as applying disinfectant and medicine to the wound. Likewise, rehabilitation is important that it can make a good environment to develop physical, psychological, social and potential ability for patients who have disabilities from various diseases and accidents. The portion of the population over 65 will nearly triple between 1980 and 2030 as a result of aging Baby Boomers and brings challenges to the health care system. The more multiple chronic conditions occur, the more requirements of rehabilitation increase. However, human resources in the medical field are limited. Furthermore, the characteristics of rehabilitation are labor-intensive and time-consuming, which makes a high cost burden. A sensor can be a solution to these increasing requirements instead of healthcare providers because the sensor can provide feedback to the patients, and the feedback to the patient could reduce their need to visit a hospital for diagnosis and assessment.

With sensor technology getting better, the size of the sensor is compact and many functions are integrated. Especially, wearable sensors which have capabilities of physiological, biochemical and a motion sensing are usually used for rehabilitation applications. Wearable sensors can be utilized in remote sensor monitoring applications such as wellness, safety, home rehabilitation, treatment efficacy, and early detection [1].

The purpose of this thesis is to develop rehabilitation application for the framework of a remote medical enhancement system. We chose two wearable sensors such as 6 degree of freedom inertial measurement unit (6-DOF IMU) and electromyography (EMG) sensor, and propose rehabilitation applications related to the early detection of disorders and home rehabilitation.

Contributions in this thesis are follows. First, we propose a novel system for detecting in-sleep stroke by using the 6-DOF IMU sensor. The system could detect hemiparesis in stroke symptoms by detecting abnormal activity ratio of left and right side during sleep. Second, we test reliability of Surface EMG (SEMG) pattern recognition by a machine learning and discuss appropriate SEMG application for rehabilitation.

An application related to early detection of disorders will be handled in Chapter Ⅲ, and the application related to co-contraction EMG for rehabilitation will be covered in Chapter Ⅳ.

II. Background – Current Wearable Sensor Technology

Wearable sensors are unobtrusive and small devices that can sense various physiological signals from the body such as electrocardiogram (ECG), blood pressure, body temperature, respiration rate, oxygen rate, heart rate, skin conductivity, heart sound, blood glucose, electroencephalogram (EEG), body movement and EMG [2].

Wearable sensor technology has been developed to monitor patients over a long time, and has the potential to be a new diagnosing tool in many clinical applications [3]. Previously, wearable technology focused on the development of wearable sensors. Recent wearable technology is focused on home-based applications such as telemedicine, home monitoring, and smart homes. The applications are categorized as follows [1].

1) Wellness: monitor physiological data and activities of daily living (ADL) in the long-term for encouragement of active and healthy lifestyle. Many wearable physiological sensors are used to monitor disease symptoms for prevention. For example, LiveNet which was developed by MIT wearable computing group used 3-D accelerometer, ECG, EMG, galvanic skin conductance sensors to monitor critical status such as a shivering in soldier, and detecting Parkinson symptom and Epilepsy seizure for maintaining wellness [4].
2) Safety: detect emergency events such as falls and epileptic seizures, and it sends messages to a caregiver or an emergency response team. A fall event is detected by wearable sensors consisting of a 3-D accelerometer. Federico et al proposed fall detection system combines 3-D accelerometer and barometric pressure sensor to increase accuracy of fall detection [5]. An epileptic seizures event is detected by physiological sensor such as an EEG, and 3-D accelerometer was complementary to EEG [6].

3) Home rehabilitation: facilitate the implementation of rehabilitation exercise programs in the home. Philips Research proposed stroke rehabilitation exerciser wearing on the relevant limbs, and accelerometer, magnetometer and gyroscope sensor are used to determine posture of patients and showed feedback by auditory and visual cues [7]. Recent rehabilitation trends use virtual reality (VR) technology. VR-based interactive games enhance motivation to rehabilitate their arm in post-stroke patients [8], and the VR-based rehabilitation in post-stroke patients is effective [9].
4) Assessment of treatment efficacy: uses as a quantitative tool of assessing treatment efficacy. Wearable sensors can provide accurate and objective measures of symptoms. For example, an activity data in daily life from 3-D accelerometer is associated with severity of Parkinson's disease patients. The activity data from 3-D accelerometer could be used as an assessment for evaluating a severity of Parkinson's disease [10].
5) Early detection: detect change in status of patients requiring clinical intervention. The purpose is to prevent worsening of clinical status in patients with pulmonary disease. Multi wearable sensors such as SpO2, activity, temperature, microphone and ECG sensor are combined and monitored a progression of chronic obstructive pulmonary disease, which is called respiratory inductive plethysmography (RIP) [11].

III.Stroke early detection by accelerometer and gyroscope

3.1 Introduction

In the hours following the onset of stroke, neurological deterioration (ND) occurs and it affects to the severe brain injury. ND is often called as different disease names such as evolving stroke, progressing stroke, and deteriorating stroke [6]. First ever ischemic stroke showed ND with higher prevalence rate, 31%, 38 patients among 121 patients [7]. One-third of patients with acute ischemic stroke also showed neurologic deterioration, which is usually associated with significant worsening of neurologic function and impaired ability to perform activities of daily living [8]. To prevent the progression of ND, many predictors of ND are researched. For example, the predictors are demographics, past medical history, neurological and clinical examination, laboratory analyses and radiographic findings [9]. However, monitoring the predictors is not appropriate in monitoring stroke in real-time even during sleep. Kim et al. asserted that ischemic stroke during sleep is associated with worse functional outcomes [13]. This is called wake-up stroke (WUS) which the patient is normal before sleep but wakes up with neurological deficits in the morning [14]. The major problem of WUS is hard to find out when stroke is onset. If stroke treatment time is passed over 3 hours, it increases bleeding complications and impairments in stroke patients. To monitor WUS, we suggest a motion sensor system which has a 6 degree of freedom inertial measurement unit (IMU) for a real-time stroke onset monitoring system. When a stroke occurs, it causes hemiparesis 80% in the worse functional outcomes. The motion sensor system monitors hemiparesis to detect stroke. The system based on accelerometer and gyroscope is wearing on each wrist, and it monitors activity ratio of left and right side of arms. The features that the activity ratio value of left and right side in normal person is close to even, and the system gives a warning alarm to caregiver and medical helper when it detects abnormal activity ratio value resulted from acute stroke patients. Eventually, our motion sensor has advantages for detection of in-sleep stroke in real-time monitoring, cost-effective, easy to wear, and convenient.

3.2 Background

3.2.1 Stroke

Stroke is the third leading cause of death in the United States. More than 140,000 people die each year from stroke in the United States, and the risk of having a stroke is more than doubles each decade after the age of 55 [12]. There are three types of stroke: ischemic, hemorrhagic, and transient ischemic attack [13]. An ischemic stroke occurs when an obstruction blocks a blood vessel that supplies blood to the brain. This type of stroke represents occurs in more than 80% of stroke patients. A hemorrhagic stroke occurs when a blood vessel ruptures because of tissue injury. A transient ischemic attack is caused by temporary clot. A stroke commonly develops complications such as motor disturbance. A lack of blood to the brain can cause stroke patients to be paralyzed on one side of body, or lose control of certain muscles in the face or in one arm [14]. Furthermore, the risk of recurrent stroke after a first-ever stroke was 30% by 5 years, about nine times the risk of stroke in the general population [15]. In stroke treatment, neuroimaging such as a CT scan or an MRI is conventionally recommended for an accurate diagnosis of the stroke type [16]. The National Institutes of Neurological Disorders and Stroke (NINDS) recommended thrombolytic therapy for acute ischemic stroke within three hours in 1995, and this was approved by the Food and Drug Administration (FDA) in 1996. Otherwise, thrombolytic therapy in patients who were treated after three hours increases the risk of bleeding complications such as intracerebral hemorrhage (ICH) [17, 18]. Stroke patients must avoid risk factors such as high blood pressure, smoking, diabetes, carotid arteries, poor diet, obesity, and alcohol and drug abuse. Continuous management of the stroke is necessary to prevent a recurrent stroke.

3.2.2 Accelerometer

An accelerometer is a device that detects and measures acceleration. Acceleration is defined as the rate at which an object changes velocity. An accelerometer can measure not only acceleration but also any force such as shock, vibration, rotation and tilting. The basic and simplest accelerometer is the spring mass system using basic principles which are Newton's law relating force and acceleration (F=ma) and Hooke's law relating force and spring action ($F = k\Delta x$). A mass connected to a spring in the spring mass system is shown in Fig. 1. If the system undergoes acceleration, there will be a resultant force equal to ma by Newton's law. This force makes the mass compress or expand the spring under the constraint that F = ma = kΔx. The acceleration a is expressed as $a = \frac{k\Delta x}{m}$. In commercial accelerometers, piezoelectric, piezoresistive and capacitive components are used. In recent years, micro electromechanical systems (MEMS) accelerometers were developed for its as small size and applicability. More recently, multi-axis MEMS accelerometer was used for lower power, compact and robust sensing. Measuring SI unit of accelerometer is m/s^2 or g (gravity force). The gravity force affects the accelerometer at 1g on the Earth's surface. To obtain the acceleration due to motion with respect to Earth, gravity off set must be considered. We used a 3-axis MEMS accelerometer sensor which removed gravity component. And also, we converted 3-axis accelerometer data to Euclidean distance (ED) which represents the moving distance owing to the 3-axis acceleration per 0.01 second. The ED was used for indicating an intensity of 3-axis acceleration because movement could be happened in all directions.

ED commonly used for measuring distance between point p and q.

$$\text{Distance } D(p,q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \cdots (p_n - q_n)^2} = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2}$$

(n : number of axis)

We convert acceleration to distance per 0.01 second in the accelerometer sensor, and it represents $(p_i - q_i)$. After converting to distance data from accelerometer data, we extracted ED component per 0.01 second.

$$S = V_o t + \frac{1}{2}at^2 \quad (\text{S : distance},\ V_o \text{ : initial velocity},\ a \text{ : acceleration},\ \text{t : time})$$

$$S = \frac{1}{2}a(0.01)^2 \quad (V_o : 0,\ t : 0.01)$$

$$ED = \sqrt{(S_x)^2 + (S_y)^2 + (S_z)^2} = \sqrt{(\frac{1}{2}a_x(0.01)^2)^2 + (\frac{1}{2}a_y(0.01)^2)^2 + (\frac{1}{2}a_z(0.01)^2)^2}$$

(S_x : distance in x-axis, S_y : distance in y-axis, S_z : distance in z-axis

a_x: acceleration in x-axis, a_y: acceleration in y-axis, a_z: acceleration in z-axis)

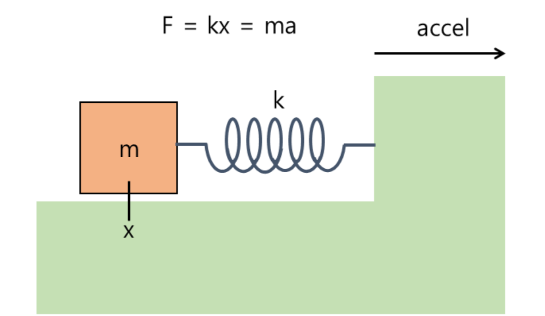

Figure 1. Principle of operation in accelerometer

3.2.3 Gyroscope

A gyroscope is a device to measure orientation based on the principle of angular momentum. Two fundamental properties of the gyroscope are rigidity in space and precession. The rigidity in space means that once the gyroscope is spinning, it tends to remain in its position and resists being moved, as a consequence of Newton's first law of motion. Precession is a change in the direction of the axis of a rotating object and is the result of torque applied about an axis that is not aligned with its spin axis. The output modes of gyroscopes are angular rate (rad/s), Euler angle and quaternion. Euler angle has the advantage of intuitive understanding because it shows each angle axis. However, Euler angle has a gimbal lock problem that 3-dimension rotating axis parallels and it loss of one degree of freedom. Quaternion consists of four elements; three imaginary numbers and one real number. The Quaternion are commonly denoted as $\mathrm{q} = q_0 + q_1\mathrm{i} + q_2\mathrm{j} + q_3\mathrm{k}$, where $i^2 = i^2 = i^2 = i * \mathrm{j} * \mathrm{k} = -1$. Quaternion information is [q_0, q_1, q_2, q_3]. Quaternion is useful in the calculation of rotation without gimbal lock problem. Quaternion information represents current position per 0.01 second. We get rotate vector $(\mathrm{X}, \mathrm{Y}, \mathrm{Z})$ from (1, 1, 1) by quaternion. The process of getting rotate vector is follows.

$$\mathrm{q} = q_0 + q_1 i + q_2 j + q_3 k$$

$$\text{unit q} = \frac{q}{\|q\|} = \frac{q}{\sqrt{q^* q}} = \frac{q}{\sqrt{{q_0}^2 + {q_1}^2 + {q_2}^2 + {q_3}^2}} = u_0 + u_1 i + u_2 j + u_3 k$$

$$\text{Rotation matrix } \mathrm{R}(\text{unit q}) = unit\ q \ \times unit\ q^* =$$

$$\begin{bmatrix} {u_0}^2 + {u_1}^2 - {u_2}^2 - {u_3}^2 & 2u_1u_2 + 2u_0u_3 & 2u_1u_3 - 2u_0u_2 \\ 2u_1u_2 - 2u_0u_3 & {u_0}^2 - {u_1}^2 + {u_2}^2 - {u_3}^2 & 2u_2u_3 + 2u_0u_1 \\ 2u_1u_3 + 2u_0u_2 & 2u_2u_3 - 2u_0u_1 & {u_0}^2 - {u_1}^2 - {u_2}^2 + {u_3}^2 \end{bmatrix}$$

$$\text{Rotate vector } \mathrm{V} = (\mathrm{X}, \mathrm{Y}, \mathrm{Z}) = [R(unit\ q) \times [1,1,1]]^T$$

After getting 3-dimensional rotate vector, we extract rotation distance per 0.01 second by using ED method.

$$\text{Rotation distance} = \sqrt{(X_{n+1} - X_n)^2 + (Y_{n+1} - Y_n)^2 + (Z_{n+1} - Z_n)^2}$$

3.2.4 Receiver operating characteristic (ROC) curve

A receiver operating characteristic (ROC) curve is an effective method of evaluating the performance of diagnostic tests. The ROC curve is a plot of true positive rate along the y-axis versus false positive rate along the x-axis as shown in Fig. 2. The terminology and deviation of the true positive rate and false positive rate are shown in Fig. 3. Each point on the ROC curve represents a true positive rate/false positive rate pair corresponding to a particular decision threshold. The closer the ROC curve is to the upper left corner, the higher the overall accuracy of the test [19].

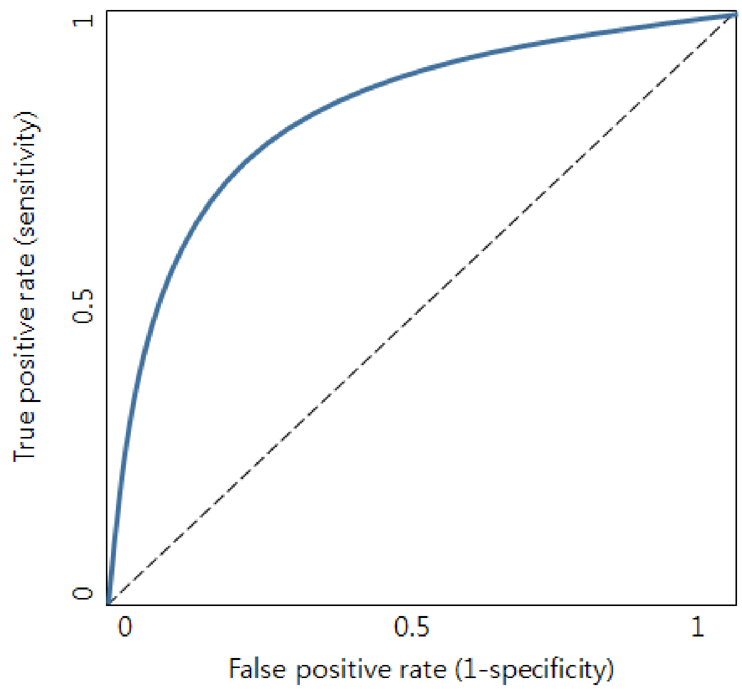

Figure 2. ROC curve

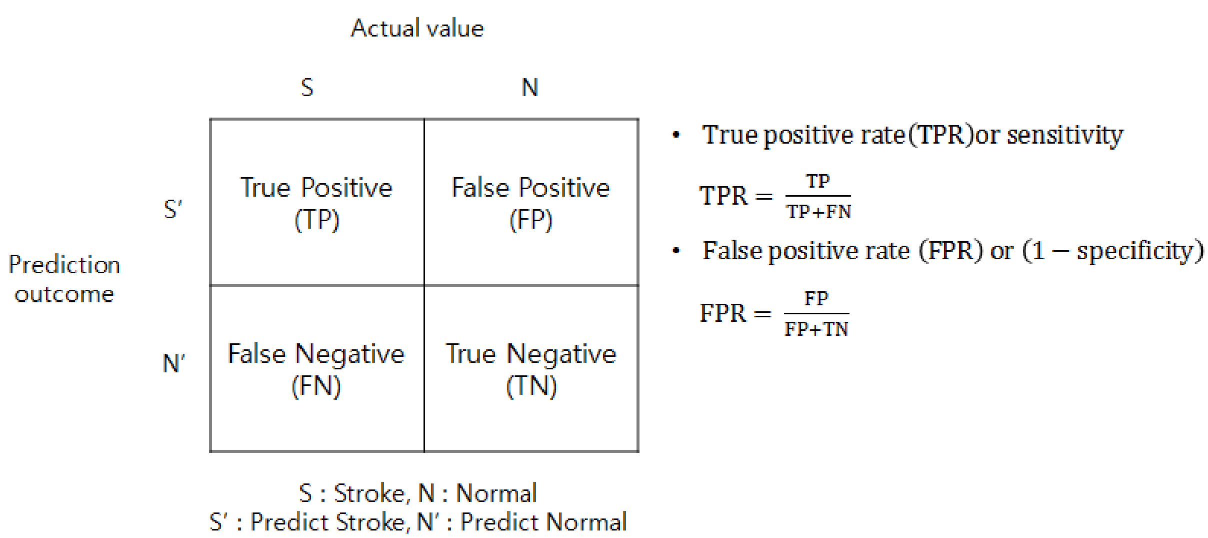

Figure 3. Terminology and derivations of TPR and FPR

3.3 Proposed approach for early detection of in-sleep stroke

We proposed a motion sensor system for detecting stroke by analyzing sleep motion from acceleration and gyroscope sensors worn on each wrist. Sleep motions are analyzed by focusing on the activity ratio of the left and right arms of the subjects in thirty normal people and four stroke patients with hemiparesis. The overall process of processing data is shown in Fig. 5. We made suspected multiple features which could distinguish between normal people and stroke patients from the two sensors, and selected activity thresholds that a difference of median value between normal people and stroke patients are biggest in each feature. After that, the performance of each feature is evaluated by ROC curve which was made by changing stroke thresholds from 0 to max value of each feature in normal people. This system was evaluated with sliding window methods by changing the parameters of the window and sliding window time to apply to the early detection of stroke system in real-time.

1) Motion sensor

We developed a wearable frame on the wrists and ankles without inconvenience in wearing and in the sleep environment as shown in Fig. 4. We used a wireless AHRS EBIMU24GV2 module from E2BOX company in Korea. This module has 9-DOF sensors and a high-precision algorithm for position calculation and can communicate with the receiver over 2.4GHz wireless broadband. The size is 32mm X 24mm and the sampling rate is 100Hz. In this module, a 3-axis accelerometer and gyroscope data were used to detect sleep features. We used accelerometer data that removed the gravity component and gyroscope data that was expressed in quaternion form.

2) Process of data processing

The ED and RD data from the accelerometer and gyroscope sensors are integrated per sec, and we called the proportional integral mode (PIM) data sorted data. The PIM data is needed to apply the sliding window method which is time based. We set the activity threshold to consider activity data when a motion occurs, and use the PIM data over the threshold. The performance of the motion sensor for stroke detection is evaluated by ROC curve. True positive rate means stroke detection rate in stroke patients with hemiparesis, and false positive rate means stroke detection rate in thirty normal people. The performance could be changed according to requirement of some system. The detail process of data processing consists of four processes.

- Make multiple features:

  Multiple features are made from ED and RD and consider 16 features as shown in Table 1. Each feature is extracted on each time window. The PIM data was made by integration per second of ED or RD. When the PIM data is over the activity threshold, the raw data of the PIM data such as ED and RD and the PIM data become an inspection of domain. The domain of feature 1, 2 and 3 are ED or RD, and find maximum, median and mean value in the domain within the time window. Domain of feature 4, 5, 6, 7 and 8 are ED_PIM or RD_PIM within time window. Feature 4 means a count number over the activity threshold. Feature 5, 6 and 7 find a maximum, median and mean value in the PIM domain.

Features	ED features	RD_features
1	ED_max	RD_max
2	ED_median	RD_median
3	ED_mean	RD_mean
4	ED_PIM_frequency	RD_PIM_frequency
5	ED_PIM_max	RD_PIM_max
6	ED_PIM_median	RD_PIM_median
7	ED_PIM_mean	RD_PIM_mean
8	ED_PIM_sum	RD_PIM_sum

Table 1. Multiple features from accelerometer and gyroscope sensor data

- Make ratio value :

A ratio value of the left and right features is core data for this system. If only a ratio value such as Left feature/Right feature is used, asymmetric value could not be an objective feature value. To compensate, we took log function and absolute function, which converts the asymmetric ratio value to a symmetric ratio value.

$$\text{The ratio value} = |\log(\text{Left feature}/\text{Right feature})|$$

- Find activity thresholds:

The ratio data in ED_PIM feature ranges from 1.5×10^{-5} to 3.5×10^{-3}, the ratio data in RD_PIM feature ranges from 0 to 7. We selected thresholds for satisfying the maximum median difference between normal people and stroke patients according to the each feature. Two-hundred thresholds cases were analyzed by changing the threshold value from $1\times$ unit to $200\times$ unit (ED ratio unit : 1×10^{-5}, RD ratio unit : 1×10^{-2}).

- Find stroke thresholds:

This process is to find the best feature and stroke threshold which distinguish between stroke patients and normal people. To find the best feature and stroke detection thresholds, we used receiver operating characteristic (ROC) curve. The ROC curve was drawn by changing the stroke threshold and a point of true and false positive rate are plotted each the stroke threshold in each feature. The stroke threshold ranges are from 0 to maximum activity ratio value in each feature in normal people. A hundred of the stroke thresholds are used for drawing ROC curve in each feature. After plotting ROC curve of each feature according to the sliding window parameter, we selected the best feature from ED and RD features by considering criterion of cut-off value decision. The criterion is follows.

$$A\ criterion\ of\ cut - off\ value\ decision :$$

$$\text{False positive rate } \leq 0.1 \text{ and Maximum True positive rate}$$

3) Stroke detection by sliding window method

To detect stroke during sleep, we used sliding window method which monitors whether sleep motions are within the time window represent a stroke or not. We designed time window of 30 minutes and 60 minutes, and sliding window times of five and 10 minutes. Stroke could be treated within 3 hours by the sliding window method because the worst case of stroke detection is after 30 minutes in the 30 minutes time window and 60 minutes in the 60 minutes time window. We tested four combination conditions; 30/5, 30/10, 60/5, 60/10 (Window time/sliding window time).

Figure 4. Picture of a motion sensor system.

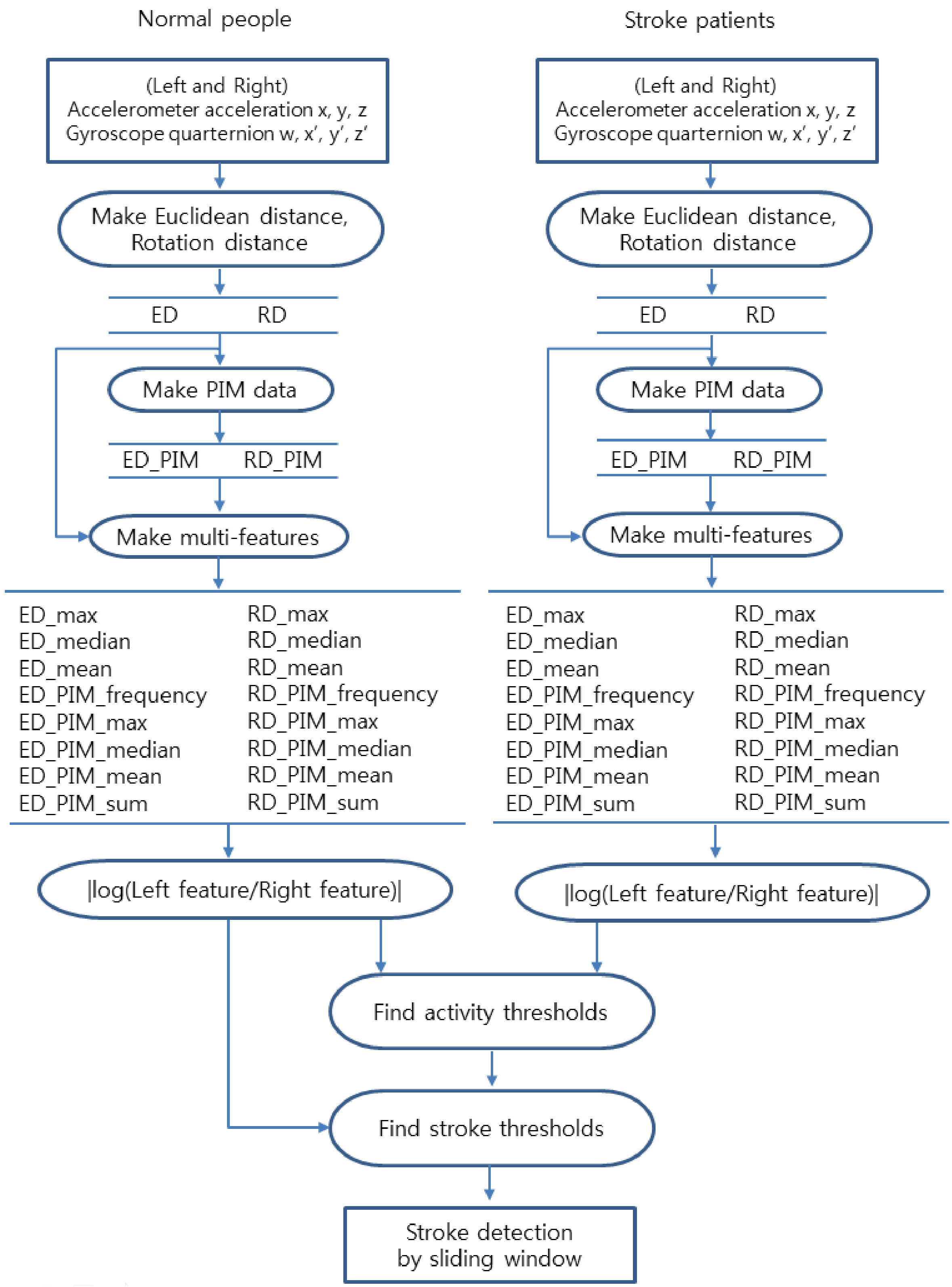

Figure 5. Data flow diagram of in-sleep stroke detection system

3.4 Results

1) Distribution of each feature value

We showed the result of distribution of each feature value considering the window and sliding window times (see Figs. 6 and 7). Multiple features which were processed with activity thresholds which are the best threshold for distinguishing between stroke patients and normal people showed that the scope of the ratio value in stroke patients is larger than the ratio value in normal people. Further, the range of the ratio value in normal people is decreased as window time and sliding window time are increased. The ratio value of RD in normal people is smaller than the ratio value of ED in normal people, which means RD activity represents more even activity in both sides.

2) Result of stroke detection

After determining activity thresholds according to the features, we evaluate a performance of each feature by receiver operating characteristic (ROC) curve.

ROC curve of ED and RD feature considering sliding window parameter is shown in Figs. 8 and 9. As window and sliding window time in sliding window parameter are increased, the ROC curves in each feature are close to upper left corner which means that performance of each feature is improved. Feature 4 and 8 are good and features in ED and feature 8 is the best feature in RD. We selected feature 8 (PIM_sum) and determined cut-off value by considering a criterion. If system designer want to high true positive rate in some system, false positive is increased because the performance is trade-off relationship. We set the criterion that false positive rate$\leq$0.1 and maximum true positive rate. When the criterion is considered in feature 8, the best cut-off value is on the ROC curve with 60/10 sliding window parameter as shown in Fig 10. And also, the performance of RD feature is better than ED feature because it is more close to upper left corner. When we considered feature 8 and 60/10(sliding window parameter), true positive rate representing stroke detection rate in stroke patients is shown in Fig. 11. A stroke threshold satisfying the criterion at the cut-off value is 1.5904 in ED_PIM_sum feature and 1.4062 in RD_PIM_sum feature, and the cut off value showed that a percentage of true positive rate in stroke patients is 75.48% in ED_PIM_sum and 97.12% in RD_PIM_sum feature. And also, a percentage of a false positive rate in normal people is 9.77% in ED_PIM_sum feature and 9.52% in RD_PIM sum feature. Results of true positive rate in individual stroke patient are shown in Fig 12. Serious stroke patients such as patient 1 and patient 4 showed high true positive rate in both features of ED_PIM_sum and RD_PIM_sum. Mild stroke patients such as patient 2 and patient3 showed high positive rate in RD_PIM_sum feature and relatively lower true positive rate in ED_PIM_sum feature. The result indicated that RD_PIM_sum feature from gyroscope sensor is better to detect in-sleep stroke than ED_PIM_sum feature from accelerometer sensor. However, the two features indicated promising possibility for in-sleep stroke detection because symptoms like the serious patients are showed when a stroke is occurred.

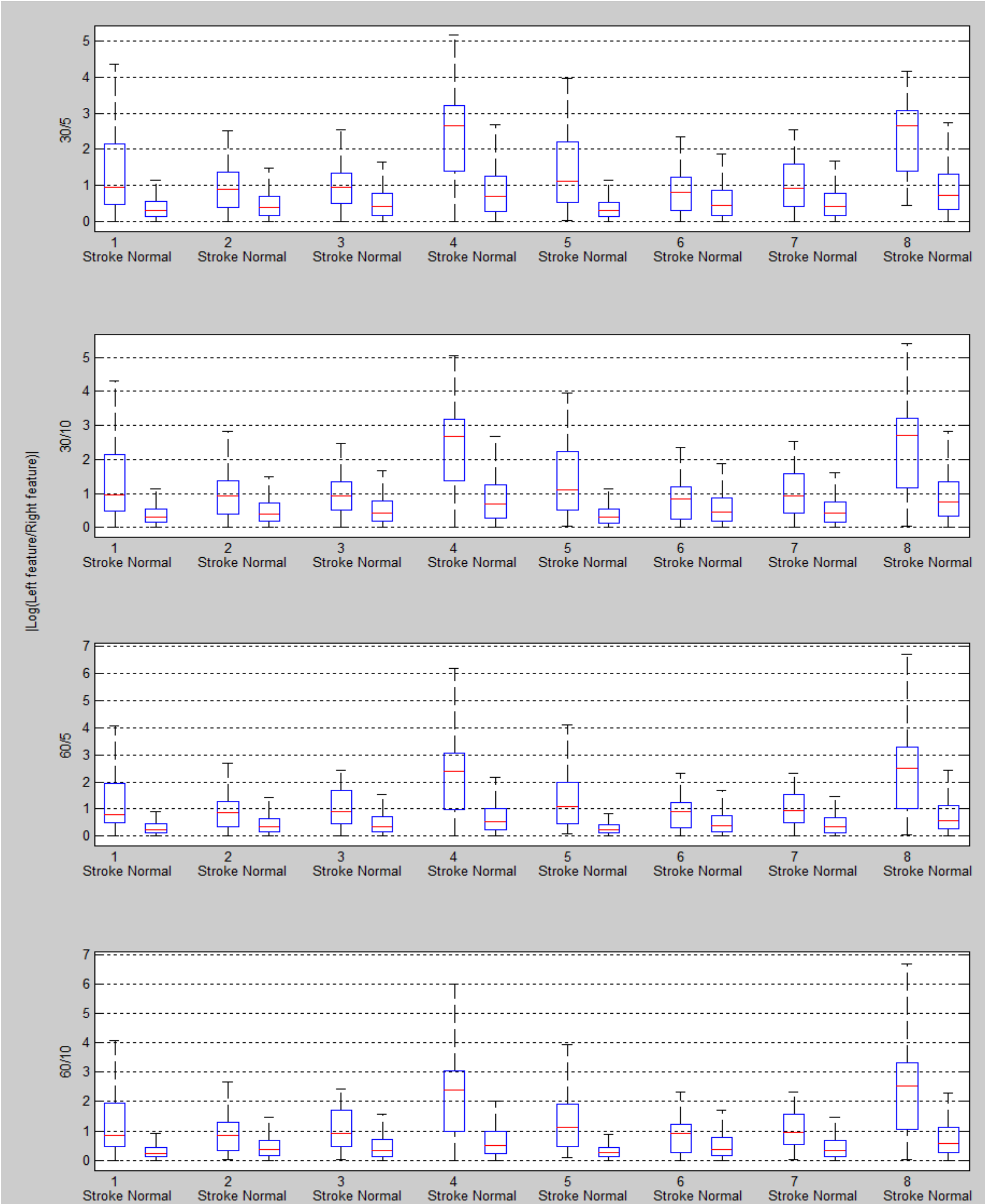

Figure 6. Distribution of ED feature ratio in stroke patients and normal people

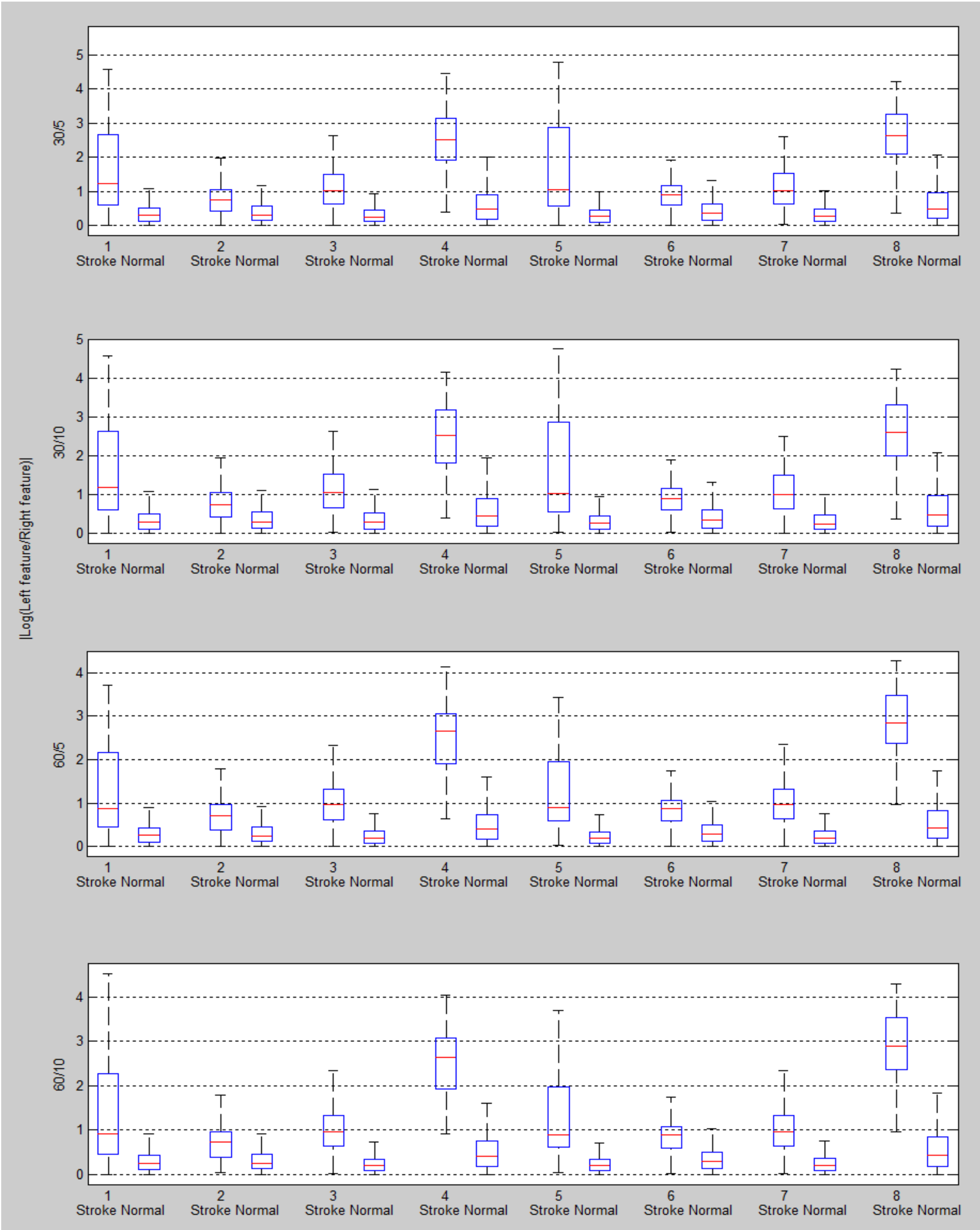

Figure 7. Distribution of RD feature ratio in stroke patients and normal people

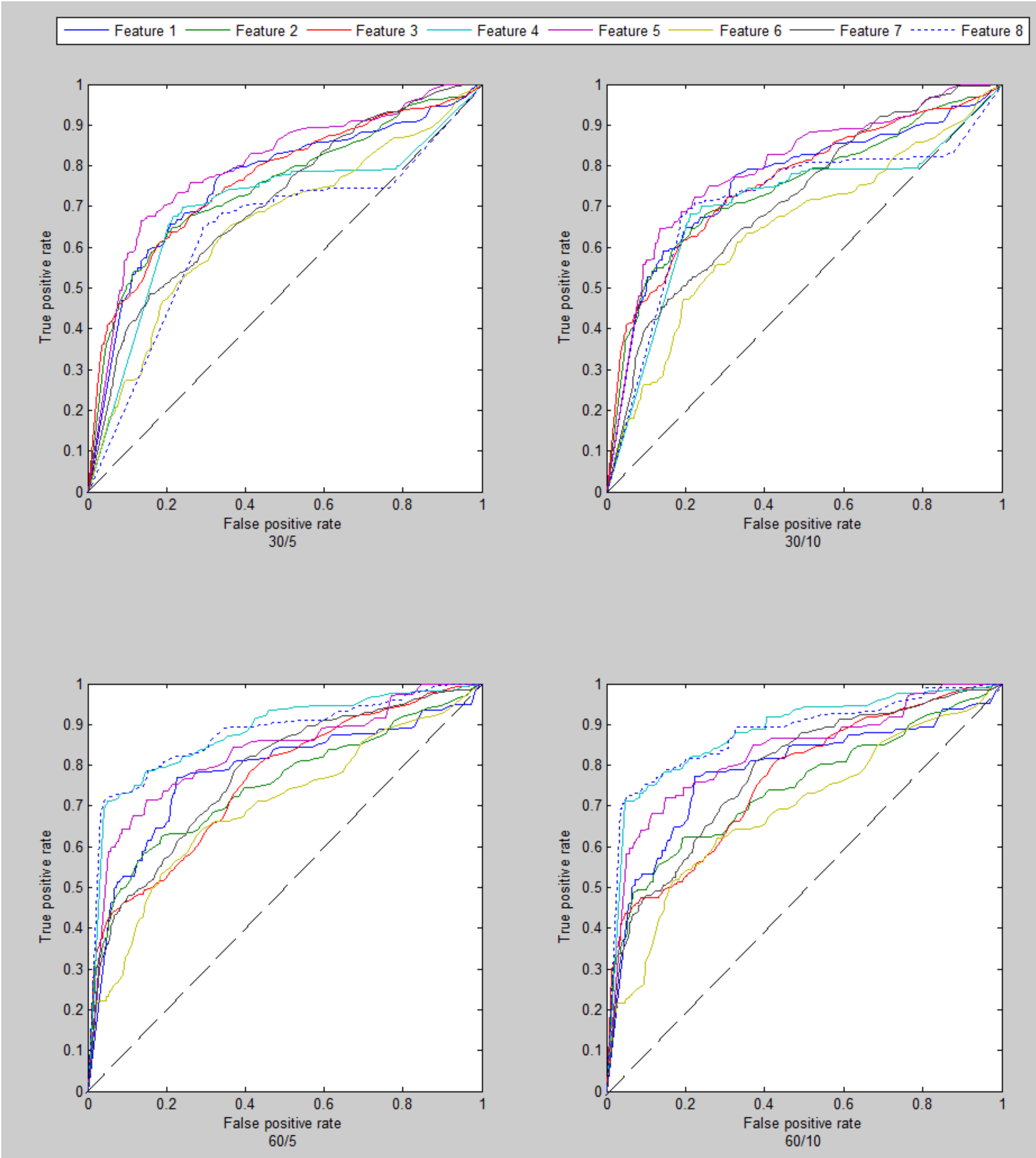

Figure 8. ROC curve of ED feature according to the sliding window parameter

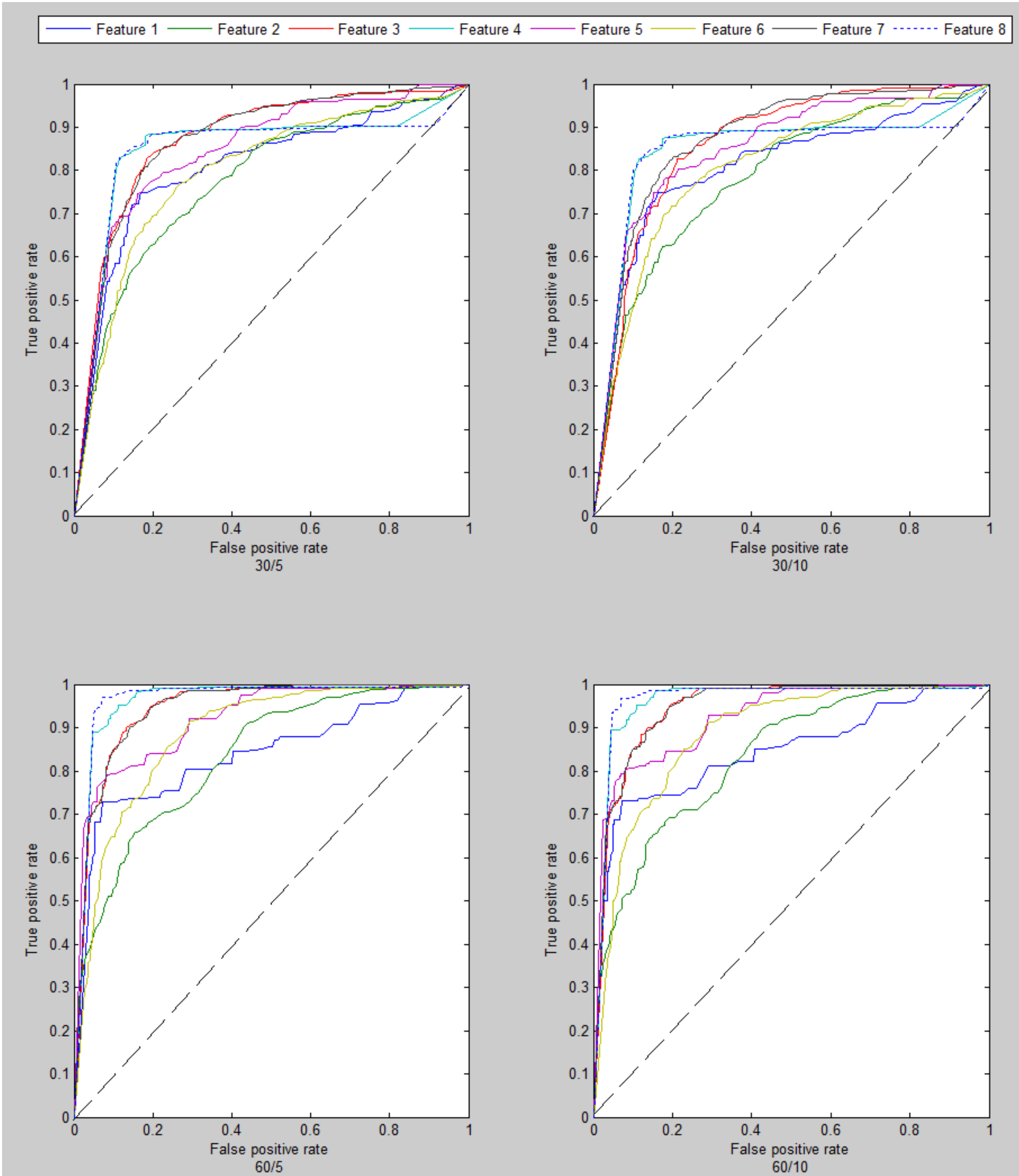

Figure 9. ROC curve of RD feature according to the sliding window parameter

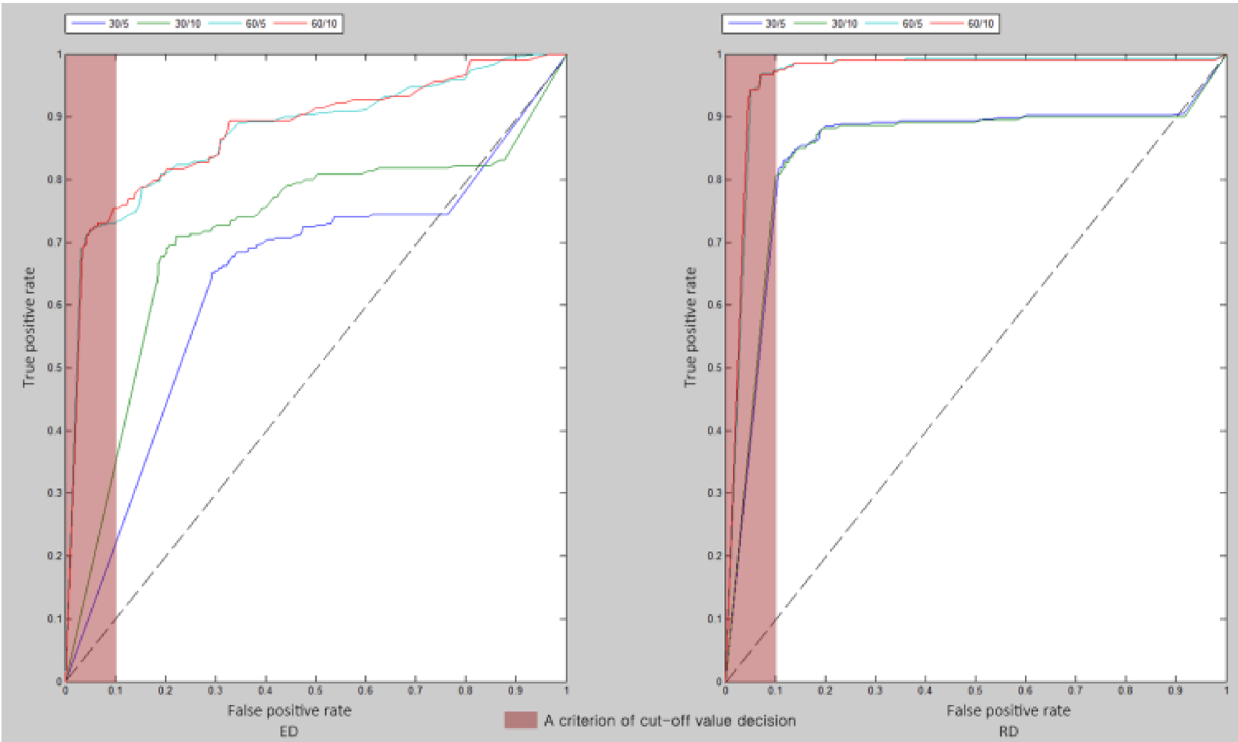

Figure 10. ROC curve of ED_PIM_sum and RD_PIM_sum feature

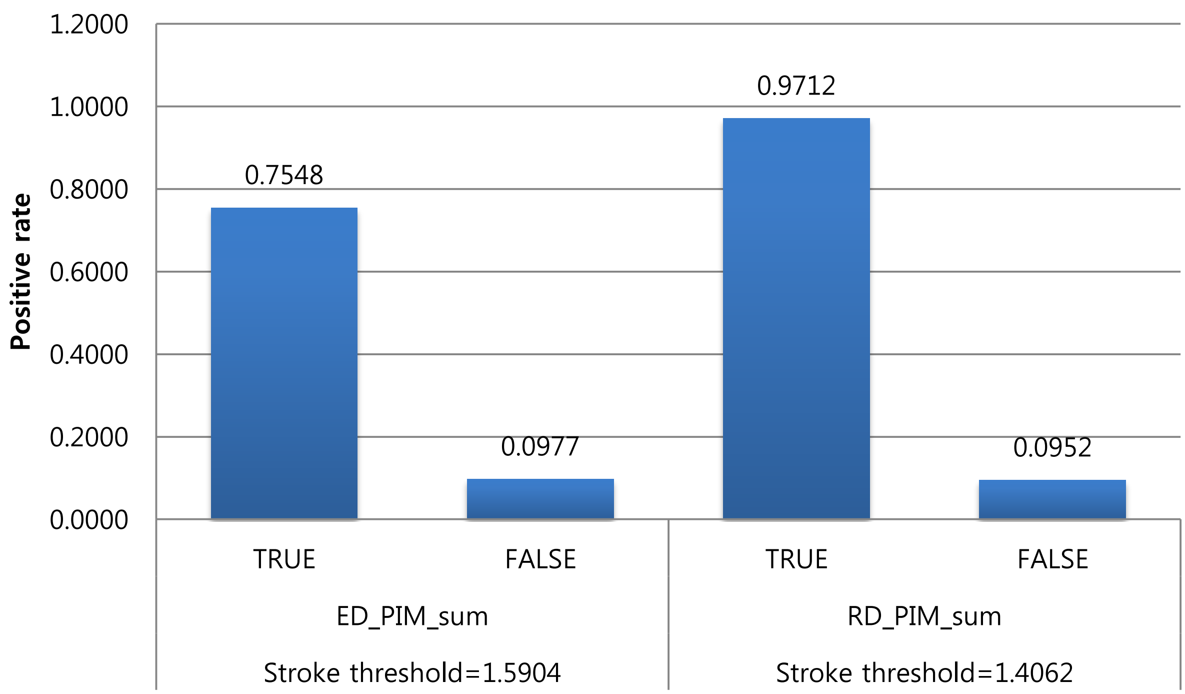

Figure 11. True and false positive rate of ED_PIM_sum and RD_PIM_sum feature

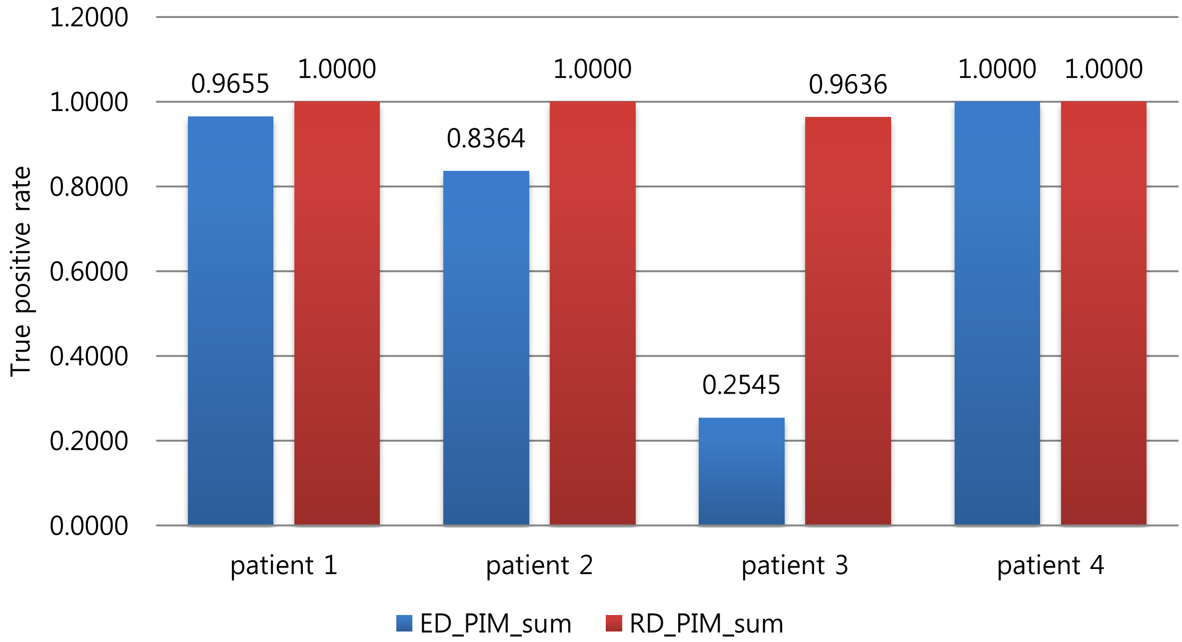

Figure 12. True positive rate of ED_PIM_sum and RD_PIM_sum feature according to individual stroke patient

3.5 Conclusion and Discussion

Slight motion is detected frequently during sleep, although there is individual variation of sleep motion. We focused on the sleep motion difference between normal people and stroke patients, and proposed a motion sensor system for in-sleep stroke detection. The distribution results of an activity ratio of left and right arm showed that stroke patients showed big abnormal activity ratio of left and right arm compared with normal people because of hemiparesis. In analysis by sliding method, performance of stroke detection is better as window and sliding window time are increased. The percentage of stroke detection results showed that ED_PIM_frequency could distinguish stroke events 75.48%, and RD_PIM_sum feature could detect stroke events 97.12%. RD features showed better performance of stroke detection than ED features, which means gyroscope sensor is more accurate in the stroke detection than accelerometer sensor. This thesis analyzed the ratio of sleep motion from the left and right arms of the subjects for detecting in-sleep stroke in real-time.

Our results showed the possibility of in-sleep stroke detection by accelerometer and gyroscope sensors. Wearable devices such as pedometers and smart-watches could be a substitute device because those devices use accelerometer and gyroscope sensor for commercialization. We will expand this system to a real-time stroke detection system and collect from many stroke patients to make the system reliable. Our motion sensor system will be an essential device for stroke patients or suspected stroke patients.

IV.Feasibility study of Surface EMG sensor

4.1 Introduction

Our activities of daily living (ADL) such as dressing, eating, feeding, bathing and showering are conducted by the combination of contraction and relaxation in muscles. If the combination of muscle activities has a problem owing to disease or accident, people cannot conduct their ADL. Electromyography (EMG) is used to diagnose and rehabilitate disorders of motor control. EMG involves detecting electrical activity from skeletal muscles and the recording and analysis of myoelectric signals [20]. EMG signals are used for rehabilitation in many medical applications such as prosthesis, EMG biofeedback and concurrent EMG feedback. In prosthesis applications, EMG signals are used to detect the intention of patients and to assist rehabilitation through prosthetic devices such as upper and lower limb. In addition, it is used in EMG biofeedback [21, 22]. EMG biofeedback provides feedback information from rehabilitation training, and provides self-motivation to achieve training goals by perceiving changes themselves. The feedback is generally delivered in the form of visual, acoustic, or haptic signals. Rehabilitation therapy in company with EMG biofeedback is effective [23-25]. Concurrent EMG feedback is used in sports rehabilitation as a strengthening tool to maintain the balance of muscle strength because, in other words, using a certain muscle excessively, can cause injuries [26]. These applications use surface EMG (SEMG) sensor. However, SEMG sensor create unavoidable noise, and the variation of SEMG signals is large, even in the same person, position and movement. This is because the combination of used muscles changes slightly each time people move. Despite the disadvantages, SEMG feedback has the advantage of direct muscle observation and the direct measurement of muscular performance. This thesis evaluates the reliability and applicability of SEMG pattern recognition for home rehabilitation.

4.2 Background

4.2.1 Muscle anatomy

Muscles are a soft tissue that performs the function of contraction. Although the basic mechanism of each muscle is the same, muscles are divided into three different muscles according to the structure.

1) *Skeletal muscle*: Is attached to the skeleton by tendon. It enables movement of the skeleton or strength.
2) *Smooth muscle*: Is the muscle of the internal organs wall. It is an involuntary muscle.
3) *Cardiac muscle (heart muscle):* Is the involuntary muscle found in the heart.

What we commonly call a muscle is skeletal muscle. Most skeletal muscles are attached directly or indirectly through tendons and aponeuroses to bones, cartilages, ligaments, or fascia or to some combination of these structures. We are focusing on muscles of the forearm. The forearm lies between the elbow and the wrist, and it performs the role of assisting the shoulder in the application of force and controlling the placement of the hand. The muscles in the forearm can be divided into two muscles the flexor and the extensor muscles depending on their position [27].

The flexor muscles are arranged in three groups as follows (Fig. 13).

1) A superficial layer group: pronator teres, flexor carpi radialis, palmaris longus and flexor carpi ulnaris.
2) An intermediate layer group: flexor digitorum superficialis.
3) A deep layer group: flexor digitorum profundus, flexor pollicis ongus and pronator quadratus.

The extensor muscles fall into three functional groups as follows (Fig. 13).

1) Muscles that extend and abduct or adduct the hand at the wrist joint: extensor carpi radialis longus, extensor carpiradialis brevis, and extensor carpi ulnaris.

2) Muscles that extend the medial four digits: extensor digitorum, extensor indicis, and extensor digiti minimi.

3) Muscles that extend or abduct the thumb: abductor pollicis longus, extensor pollicis brevis, and extensor pollicis longus.

When we move our forearm, there are many combinations of extension and flexion in many muscles of the forearm at different levels of force. It moves our body and allows specific actions by the harmony of the muscle movement.

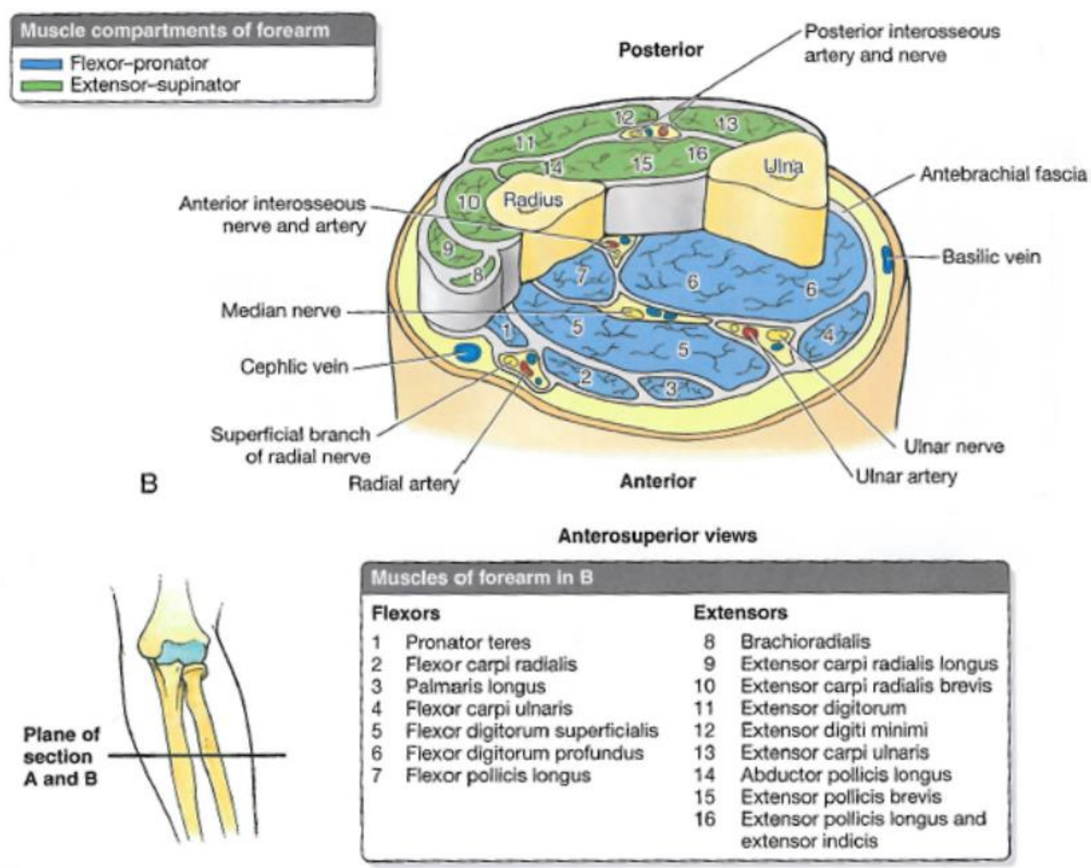

Figure 13. Anatomy of forearm [27]

4.2.2 Surface EMG

Surface EMG (SEMG) is a non-invasive technique in which electrodes are placed on the skin overlying a muscle to detect the electrical activity of the muscle. A raw SEMG recording is shown in Fig. 14 [20].

SEMG signals are sensitive to noise and proper skin preparation. Many noise reduction filters are needed for a good quality SEMG signal.

Jeffrey et al. discussed the pros and cons of SEMG [28]. SEMG provides a safe, easy, and non-invasive method for observing objective quantification of the energy of the muscle without penetrating the skin. In addition, it provides information of muscle function and dysfunction to clinicians and researchers for research of rehabilitation. Finally, the SEMG signals are obtained from muscle feedback form the patients as a reeducation form, which is called EMG biofeedback. On the other hand, the shortcoming of SEMG is that it monitors only a few muscle sites. Another possible shortcoming is muscle substitution patterns that the neuromuscular system may express the same movement using different muscle groups. A final shortcoming is cross-talk whereby a neighboring muscle group interferes with the recording. SEMG does not measure force, strength, amount of effort given, or muscle resting length. SEMG simply measures electrical activity.

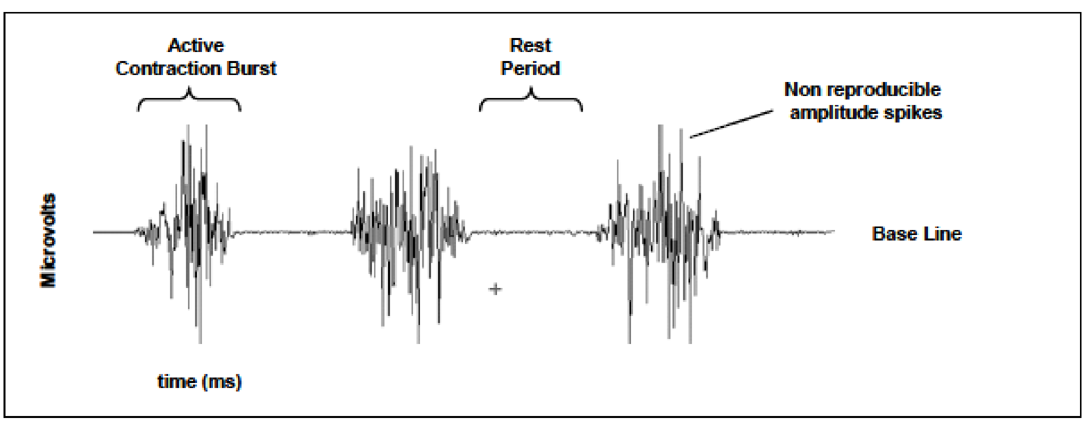

Figure 14. Raw SEMG recording of 3 contractions of the biceps brachii muscle [20].

4.3 Method

The SEMG sensor has the weakness of being inconsistent or unreliable because it detects not specific muscle but surface muscle signals. However, machine learning can complement this weakness. In this section, we verify the reliability of the SEMG pattern recognition from simple movement to complicated movement by SEMG signal pattern recognition using the machine learning method.

4.3.1 SEMG sensor

We used SEMG sensor from Biopac company. The SEMG sensor consists of a transmitter and a receiver, and it provides software for data analysis. The transmitter has two SEMG channels and transmits the sensing data to the receiver through wireless communication. The transmitter can wear on the arm or leg by strap and transmits SEMG signals to the receiver, it makes wearable SEMG system. An electrode of SEMG uses disposable Ag/AgCl electrode.

We used four SEMG sensors which make up four channels. The electrodes of SEMG sensors were placed on the four positions so that channel 1 was on the Flexor carpi radialis, channel 2 was on the extensor carpi radialis longus, channel 3 was on the Flexor digitorum profundus, and channel 4 was on the flexor carpi ulnaris as shown in Fig. 14.

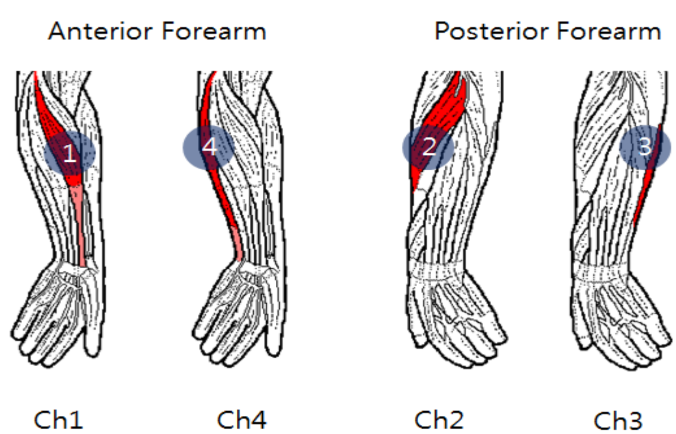

Figure 15. Channel position in forearm anatomy [29]

4.3.2 Experiment method

An Experiment was divided into two tests such as simple motion and complicated motion. Simple motion composed wrist movements such as up, down, left and right. Complicated motion composed activities of daily life such as eating a spoon, pushing a button and moving an object. In each experiment, we tested accuracy of SEMG pattern recognition by considering changes according to the time, electrode position and person. The experiment was conducted when a metronome sound was heard. The interval of the metronome sound was two seconds in the simple movement test, and three seconds in the complicated movement test. In each experiment was conducted thirty times.

4.3.3 Evaluation items

We tested the reliability of pattern recognition from a simple motion to a complicated motion by making the test and training data in Lib-SVM change. The evaluation items are as follows.

1) Motions for pattern recognition
   - Simple motion (gesture): Wrist up, down, left and right
   - Complicated motion (Activities in daily life): Eating with a spoon, Push a button, Move object.
2) Evaluation list
   - Time change
   - Electrode position change
   - Person change

4.3.4 Evaluation method

Support vector machine (SVM) is a machine learning method for detecting decision boundary which is far away as possible in two classes. We used LibSVM in SVM which is a commonly used machine learning method because its method of operation is easy and it provides a library in many program languages [30]. We used LibSVM in matlab version. Three features such as variance, root mean square and wave length were used as a data set of LibSVM.

1) Features in LibSVM :

- Variance (VAR) = $\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2$
- Root mean square (RMS) = $\sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i{}^2}$
- Wave-length (WL) = $\frac{1}{N}\sum_{i=1}^{N-1}|x_{i+1} - x_i|$

The total feature in each experiment consists of a one-dimensional array such as 1×12. The total feature has a form such as [channel1, channel2, channel3, channel4]. Each channel has three features and a form of 1×12 array such as [VAR, RMS, WL, VAR, RMS, WL, VAR, RMS, WL, VAR, RMS, WL].

2) Data set in LibSVM

LibSVM data sets consist of test set and training set. In each set, LibSVM data is made of classes and features, which expressed as a form such as [class number, N (feature number), ':', feature] as shown in Fig. 16. The purpose of the LibSVM is to distinguish classes of the data in test set by learning the data in training set. We tested accuracy of SEMG pattern recognition, which classify each motion representing class by considering various changes such as time, electrode position and person.

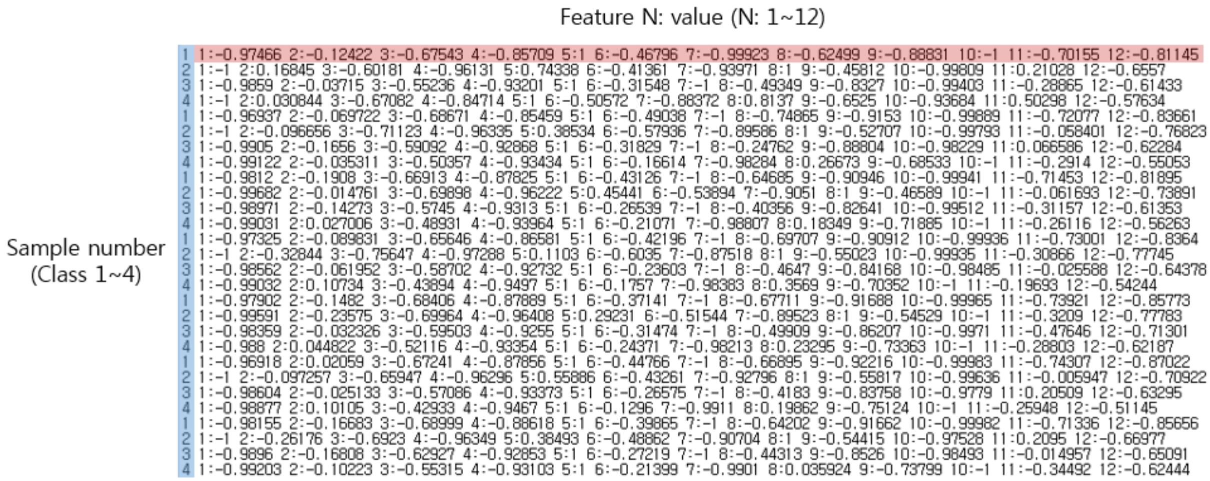

Figure 16. Dataset of LibSVM in simple motion test

4.4 Experimental Results

4.4.1 Simple motion test

1) Time change: A time change test was conducted seven times on the same electrode position at a time distance of over three hours. In SVM, test set uses the n-th experiment set and the training set uses the remaining sets except the n-th experiment set. Even though SEMG signal was acquired on the same position, there is a low accuracy of SEMG pattern recognition in the fifth experiment set as shown in Fig. 17.

2) Electrode position change: An electrode position change test was conducted as the electrode moved 5mm from side to side. In SVM, test set used the each experiment set which moved from side to side, and the training set used time change test sets in 1). The accuracy of SEMG pattern recognition was decreased considerably as shown in Fig. 18.

3) Person change: A person change test was conducted on four normal people. In SVM, test set used experiment set from four normal person, and the training set used pervious all of

experiment sets in 1) and 2). The accuracy of SEMG pattern recognition is much lower and with a large variation according to the person as shown in Fig. 19.

4.4.2 Complicated motion test

1) Time change: The experiment test method is the same to as the time change test in the simple motion test 4.4.1-1). The accuracy of SEMG pattern recognition in the complicated motion test was lower than the accuracy in the simple motion test as shown in Fig. 20.

2) Electrode position change: the experiment test method is the same as the electrode position test in simple motion test 4.4.1-2). Although the test sets used moved test sets which moved 5mm from side to side, the initial position is different slightly because marked initial position was erased. However, the result indicates that the accuracy of the SEMG pattern recognition is much lower except the pushing the button test and it is larger than the simple motion test as shown in Fig. 21.

3) Person change: The experiment test method is the same as the electrode position test in the simple motion test 4.4.1-3). The accuracy of pushing the button was 100%, and it could perfectly distinguish the button pushing movement. However, the accuracy of the other movements was much lower and it was worse than the simple motion test as shown in Fig. 22.

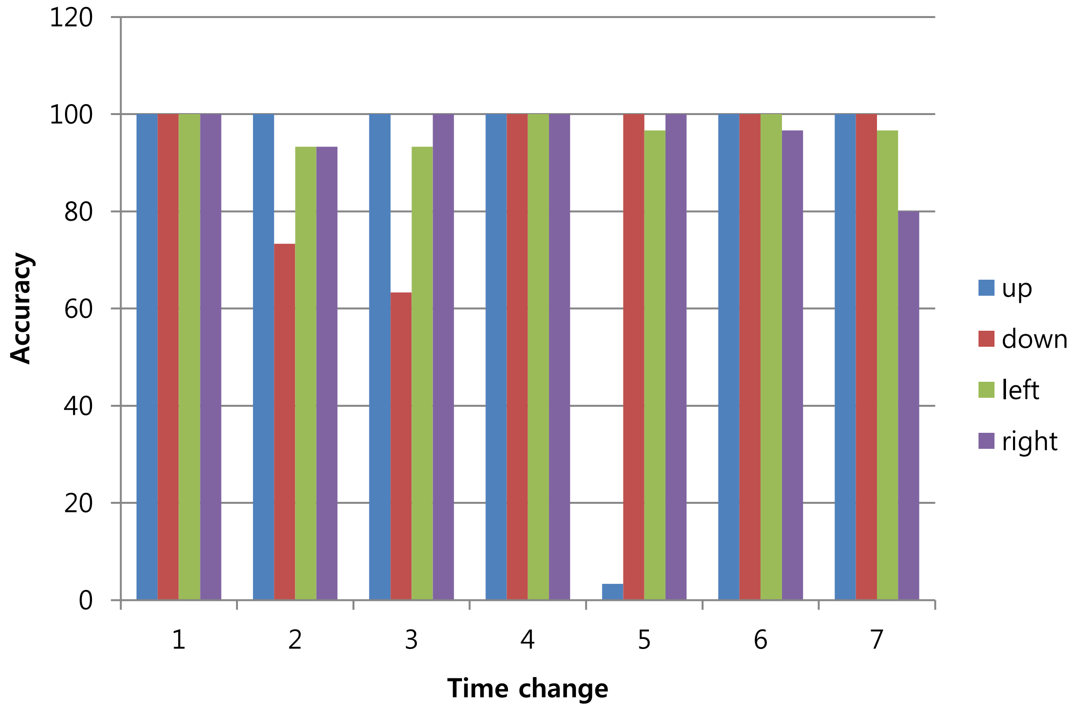

Figure 17. Accuracy of LibSVM according to the time change in simple motion

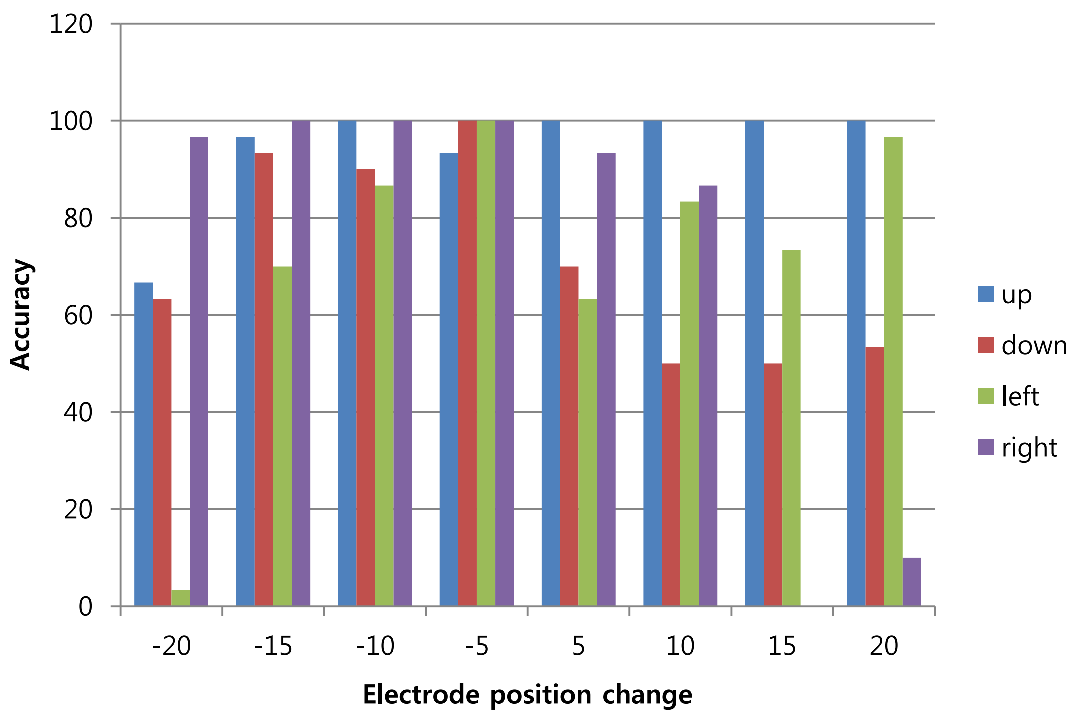

Figure 18. Accuracy of LibSVM according to the electrode position in simple motion

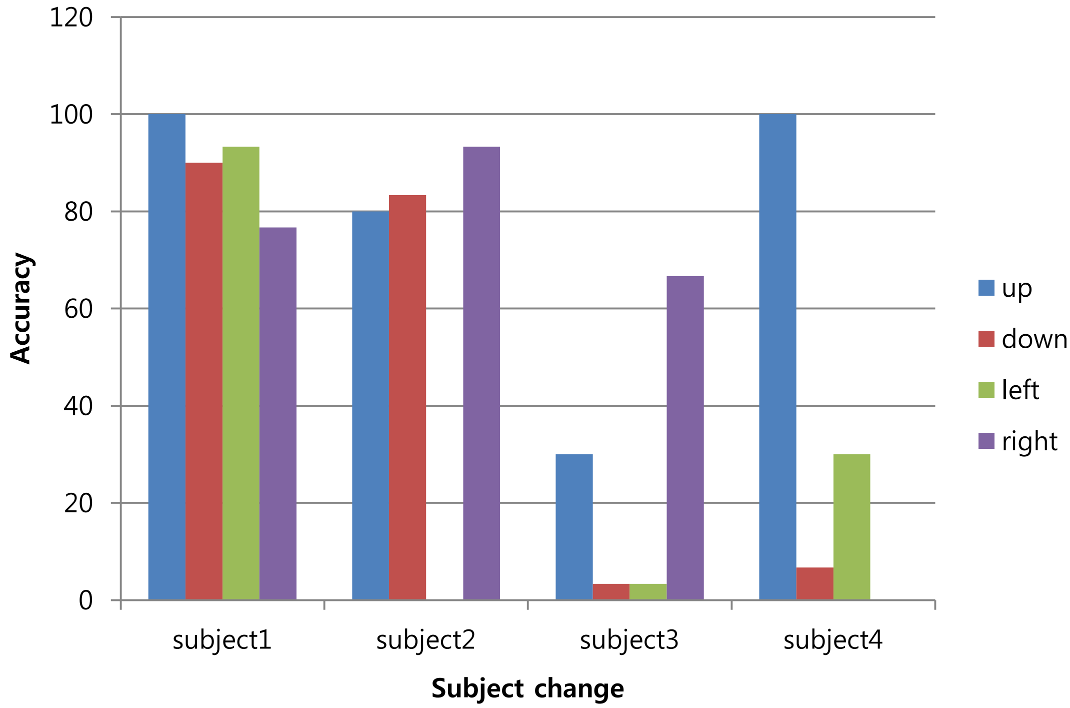

Figure 19. Accuracy of LibSVM according to the person in simple motion

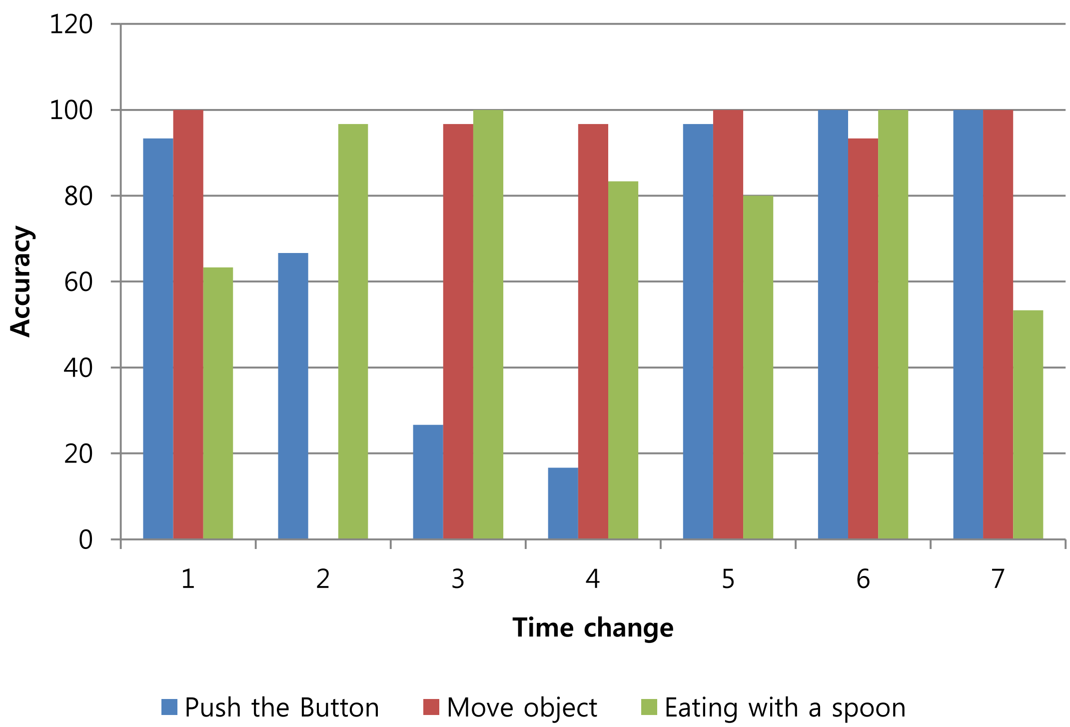

Figure 20. Accuracy of LibSVM according to the time in complicated motion

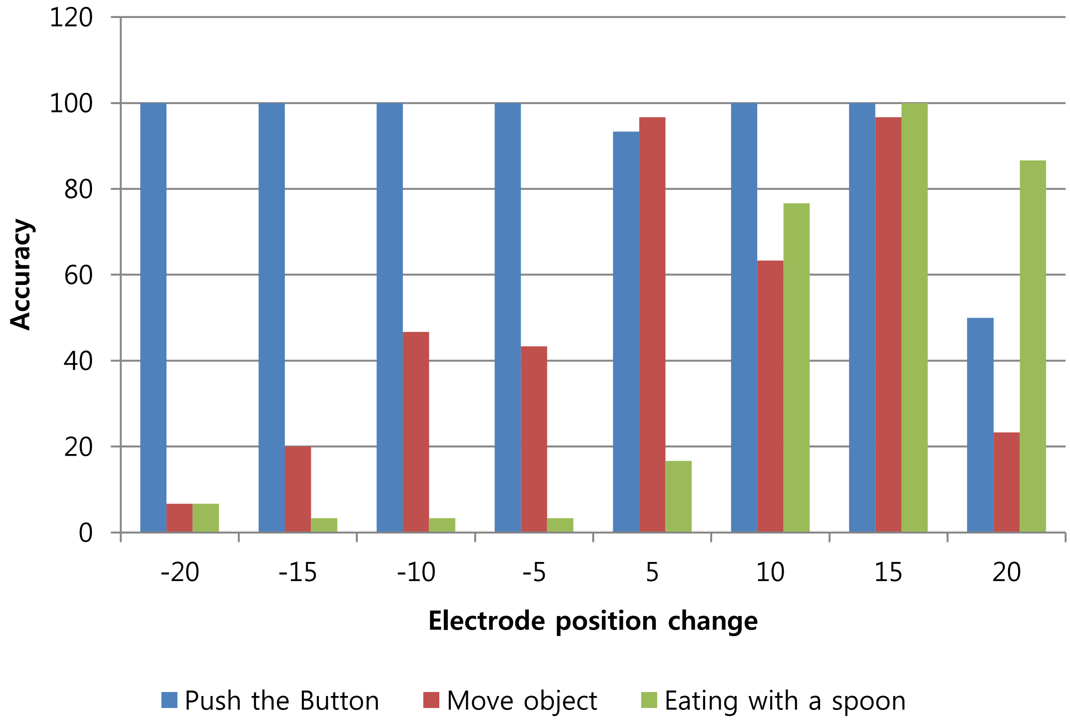

Figure 21. Accuracy of LibSVM according to the electrode position in complicated motion

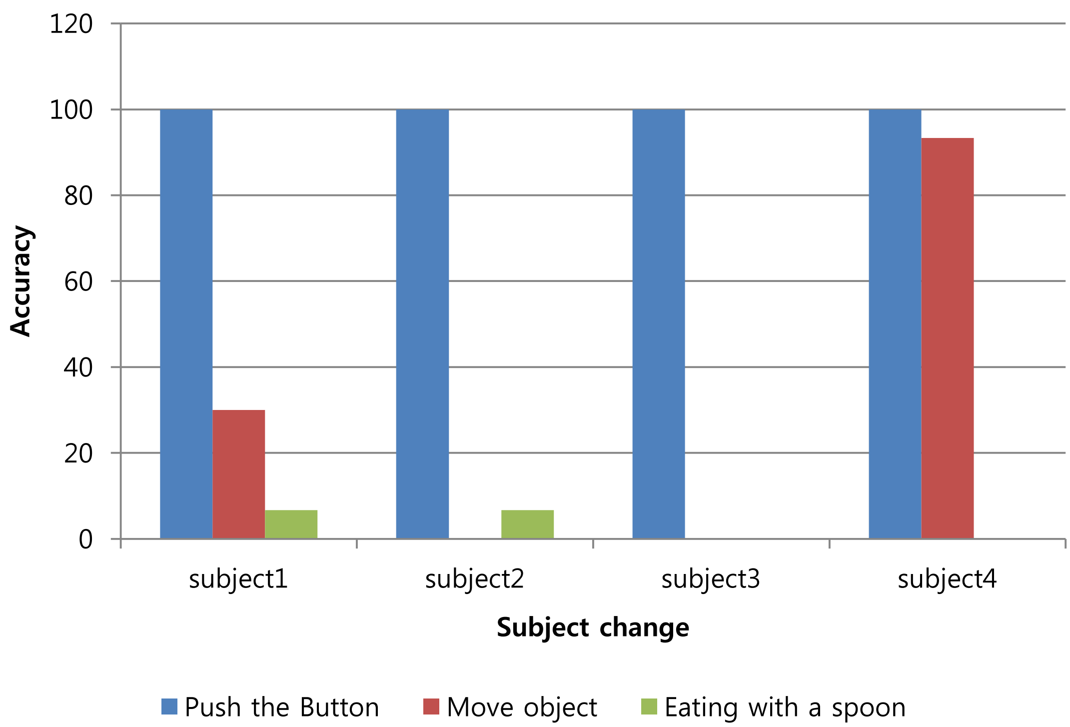

Figure 22. Accuracy of LibSVM according to the person in complicated motion

4.5 Conclusion and Discussion

We tested SEMG pattern recognition for applying rehabilitation. The overall accuracy of the EMG pattern recognition is greatly influenced by three changes such as time, electrode position and person. SEMG signal has a large variation even if the position of the electrodes is the same each time. The variation may be due to electrode conductivity and muscle fatigue. Also, the accuracy also decreased as the position of the electrodes is changed. Furthermore, the variation of SEMG signal is also large because muscle size and power is different according to each person although we performed the same movement.

The SEMG pattern recognition in simple motion test is higher than that in the complicated motion test. However, this accuracy is the result of targeting a normal person. Benedetta Cesqui et al. tested the feasibility of EMB-based pattern recognition [22]. Although EMG-based pattern recognition is feasible for detecting the intention of a normal person, it is not feasible in subjects with neurological injury such as stroke, because stroke patients do not move their muscles voluntarily. It indicates that application for rehabilitation in patients with muscle disorder is suitable for the uses of simply detecting whether a muscle is activated. Simple and meaningful application by using EMG sensor is co-contraction. When a muscle contracts, the opposite muscle relaxes to perform the movement. If the both the muscles do not perform opposite movements and contract simultaneously, it is called co-contraction. Co-contraction of antagonist muscles is a clinical phenomenon in patients with cerebrovascular accident, and hemiparesis patients show signs of co-contraction patterns across multiple joints [31, 32]. Reducing co-contraction caused by motor impairment and physical disability improves overall arm function. Wright Z.A et al. proposed myoelectric computer interface (MCI) to retrain arm muscle activation and reduce co-contraction [33]. Patients tried to move a 2-D cursor position at the center to a randomly-selected target in a center-out task, and the co-contracting muscles were mapped to orthogonal directions. The MCI improved overall arm function in the affected arm of stroke subjects by retraining arm muscle activation.

Although many other sensors such as accelerometers, gyroscopes, Kinect and so on are better and more accurate in performance, the reason why the SEMG sensor is used is that the SEMG sensor can detect the invisible movement of muscles. However, SEMG has a structural weakness in that it detects muscle groups not muscles. Also, the structure of SEMG generates noise such as crosstalk. Furthermore, same movement is expressed in different SEMG signals because a different combination of muscles can make the same movement. It indicates that the SEMG signal is inconsistent and unreliable. Therefore, SEMG application for rehabilitation is not feasible in pattern recognition applications that require high-precision, and is appropriate in co-contraction EMG application detecting an activation of a muscle.

V. Conclusion and Future work

We used two wearable devices such as 6-DOF IMU and EMG sensor, and covered rehabilitation applications such as early detection of disease and home rehabilitation. In Chapter Ⅲ, we covered a motion sensor system for in-sleep stroke detection, and it focused on hemiparesis symptoms in stroke patients. The motion sensor system could detect the activities of each arm during sleep, and we deducted the normal ratio of both arms from 30 normal people. The ratio was used as a stroke event threshold, and the test result from four real stroke patients with hemiparesis has the potential to detect stroke with hemiparesis during sleep. The results showed that the motion sensor system research is promising. The motion sensor system could detect stroke 75.48% by ED_PIM_sum feature from accelerometer sensor and 97.12% by RD_PIM_sum feature from gyroscope sensor with about 10% false positive rate in two the features. The system performance could be adjusted by changing stroke threshold according to the system requirements, but the adjustment of performance has a trade-off relationship. To improve true positive rate without increasing false positive rate, the motion sensor system needs more noise reduction filtering and processing algorithms. We will expand this system in real-time and apply it in to a real-time stroke detection system by analyzing stroke patients and normal people who are symptomatic of stroke and over 65 years of age. In Chapter Ⅳ, we dealt with the feasibility of SEMG pattern recognition. The experiment result showed that although an SEMG sensor offers direct observation and measurement of muscles, structural measuring limitations such as crosstalk noise and variation of muscle combinations in the same movement make it difficult to use in SEMG pattern recognition. Although it has potential to apply in simple motion recognition such as gesture, it varies according to changes such as time, electrode position and person. Also, it is not feasible to apply in patients with muscle disorders because they do not control their muscle correctly, which creates more variation. In the complicated motion such as ADL, the variation of SEMG pattern recognition is larger than the simple motion. SEMG pattern recognition application requires more accuracy to apply in rehabilitation application. We concluded that it is feasible to apply in co-contraction EMG application because the application checks whether a muscle is activated, which do not require high accuracy in SEMG signals.

Recent wearable sensor technology has shifted from the development of sensors to the design of systems because the size of sensors is small and they provide highly accurate sensory information. We used 6DOF IMU and EMG sensor, and proposed a rehabilitation application for early detection of stroke and home rehabilitation systems. In addition, physiological sensors and smart-watches, smart-glasses, and fitness and wellness sensors make possible new technology and life paradigms. Wearable devices will play important role in our life soon.

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요 약 문

착용 가능한 센서를 사용한 재활 어플리케이션 개발

점차 고령화 시대로 들어감에 따라 의료서비스에 대한 요구가 늘어나고 있다. 특히 노동집약적이고 장기간 치료가 요구되는 재활분야에서는 한정된 의료계 인력을 대신해서 착용이 가능한 센서로 점차 증가되는 요구를 수용할 수 있을 것이다. 우리는 3축 엑셀로미터 센서와 3축 자이로스코프 센서를 가진 6 축 관성측정장치 센서와 표면 근전도 센서를 사용하여 질병조기진단 및 집안에서 할 수 있는 재활운동과 관련된 어플리케이션을 제안한다. 첫 번째로, 우리는 6축 관성측정장치 센서를 사용하여 팔의 좌우 비정상적인 움직임 발견함으로써 수면 중 뇌졸중을 모니터링 할 수 있는 시스템을 제안한다. 정상인과 편마비가 온 뇌졸중 환자를 구별할 수 있는 특징데이터들을 센서 데이터로부터 만들고, 각 특징데이터마다 최적의 뇌졸중 판별 기준으로 슬라이딩 윈도우 방법을 사용해서 뇌졸중을 판별해 보았다. 이 시스템을 실제 편마비가 있는 환자에게 적용하였을 때, 엑셀로미터 센서 데이터로부터는 75.48%, 자이로스코프 센서 데이터로부터는 97.12% 검출할 수 있었다. 두 번째로, 일상적인 행동의 훈련을 위한 표면 근전도 신호의 패턴인식의 가능성을 검사하였다. 우리는 시간적인 변화, 전극의 위치 변화, 사람의 변화 등 여러 변수들을 고려하여 간단한 동작부터 복잡한 동작까지 실험을 하였다. 실험결과 근전도 신호의 패턴인식은 근육과 표면 근전도 센서의 구조적인 문제로 인하여 위의 세가지 변수들에 의해서 크게 영향을 받는다. 우리는 표면근전도 센서로는 동시 수축 근전도와 같은 근육의 활성 정도만 판별하는 간단한 어플리케이션에 적합하다고 결론을 내렸다.

핵심어: 재활 어플리케이션, 수면중 뇌졸중, 표면 근전도의 패턴인식, 동시 수축 근전도