August 2018
Master's Degree Thesis

Study of EMG-based Authentication Algorithm Using Artificial Neural Network

Graduate School of Chosun University
Department of IT Fusion Technology
Siho Shin

Study of EMG-based Authentication Algorithm Using Artificial Neural Network

인공 신경망을 활용한 근전도 기반
개인 인증 알고리즘 연구

August 24, 2018

Graduate School of Chosun University

Department of IT Fusion Technology

Siho Shin

Study of EMG-based Authentication Algorithm Using Artificial Neural Network

Advisor : Prof. Youn Tae Kim

This thesis is submitted to The Graduate School of Chosun University in partial fulfillment of the requirements for the Master's degree.

August 2018

Graduate School of Chosun University

Department of IT Fusion Technology

Siho Shin

This is to certify that the Master's Thesis of Si Ho Shin

has been approved by the Examining Committee for the thesis requirement for the Master's degree in IT Fusion Technology.

Committee Chairperson
Prof. Sung Bum Pan (Sign) ______________________ (Sign)

Committee Member
Prof. Keun-Chang Kwak (Sign) ______________________ (Sign)

Committee Member
Prof. Youn Tae Kim (Sign) ______________________ (Sign)

May 2018

Graduate School of Chosun University

Table of Contents

List of Figures

Acronyms

EMG	Electromyography
ECG	Electrocardiography
EOG	Electrooculogram
EEG	Electroencephalogram
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
KNN	K-nearest Neighbors
SVM	Support Vector Machine

Abstract

A study of an EMG-based authentication algorithm using an Artificial Neural Network

Si Ho Shin
Advisor: Prof. Youn Tae Kim, Ph.D.
Department of IT Fusion Technology,
Graduate School of Chosun University

Biometric authentication, which uses body parts as a password, does not require memorization and is widely used owing to its excellent security. Primarily, fingerprints, face, iris, voice, etc. are used for personal authentication.

However, when a vulnerability is found in each method, an authentication method for securing it is required. Therefore, this study proposes a personal authentication method using EMG.

EMG is a μV-sized electrical signal that occurs in the muscles as the body moves. This signal can detect muscle health, nerve abnormalities, and body movements. EMG data were acquired from the right arm after constructing multiple measurement channels. Further, the operation of holding the fist was repeated for several times while measuring the data. The EMG data were acquired using the EMG measurement module that was directly produced.

To improve the personal authentication rate, we designed a digital filter using Matlab and applied it to the EMG signals. To classify the individuals, Variance value, Mean value, Zero crossing value, Length value, and Median Frequency value parameters were extracted from the EMG signals.

The extracted parameters were classified into artificial neural networks that implemented the program for brain information processing. The model used for the artificial neural network is a feedforward neural network. The result of the EMG-based personal authentication showed 95.0 % accuracy.

요 약

인공 신경망을 활용한 근전도 기반 개인 인증 알고리즘 연구

신시호
지도교수 : 김윤태 교수, Ph. D.
조선대학교 대학원 IT융합학과

사용자 인증을 위한 패스워드 입력 방식은 해킹에 취약하다. 그래서 심전도, 근전도와 같은 생체 신호를 이용한 보안 기술이 개발되고 있다. 본 연구에서는 개인 인증 기술의 취약점을 보완하기 위해 근전도를 이용한 개인 인증 알고리즘을 제안한다. 인증률을 향상시키기 위해 인공신경망 알고리즘을 사용하였다. 이 방식은 전처리, 특징점 추출, 분류 등의 과정을 포함한다. 개인 인증은 근전도 신호로부터 다섯 가지의 특징점을 추출하여 진행하였다. 제안된 알고리즘은 실험을 통해 95.0 %의 정확도를 나타내었다. 진행하였다. 제안된 알고리즘은 실험을 통해 95.0 %의 정확도를 나타내었다.

I. Introduction

As ICT is developing rapidly, biometric-information-based authentication technology that can easily authenticate an individual using fingerprints has received particular attention [1]. Biometric authentication is a method of authenticating an individual using his/her personal biometric information and can be used anytime and anywhere. Unlike passwords, one does not have to remember any details.

Another advantage is that it is difficult to hack because it uses complex body information. Biometric authentication primarily uses personal characteristics such as fingerprint, face, vein, and iris, or personal authentication based on biometric signals such as ECG, EMG, and brain waves [2,3,4].

Biometric authentication has become attractive in IT security as the technical ability to use biometric information has improved and the investment cost for personal authentication research has increased. According to a report by the US IT market researcher Tractica, the biometric authentication market of approximately $2 billion in 2016 is expected to grow to more than $14 billion by 2025 [5]. As the market for biometric authentication grows, research on biometric authentication has been actively conducted; however, the weakness of the authentication method is becoming increasingly evident.

Recently, a case has been reported where a person has succeeded in authentication after copying a fingerprint using gelatin [6]. As such, it is possible to perform personal authentication by copying and printing around the eye for iris recognition and covering the contact lens specially manufactured on the eye. Therefore, a new authentication method is required as an alternative.

II. Key Technology

2.1. Fundamentals of biometric authentication

Personal certifications are ubiquitous in our everyday lives. We are certified on various occasions, such as when we go to work, log in to a website, when we finish work, when we return home, or when we enter a security facility.

Authentication exists in several forms. One can enter a memorized password, PIN number, or submit one's personal identification card and use a public certificate [7]. However, the current methods are disadvantageous in several aspects.

Inside the certified certificate, the user name, the authentication key, and the expiration date are included. However, it is inconvenient to reissue a public certificate every certain period, and the authentication process is more difficult than the password-based authentication method.

The PIN number input method is a method of confirming the identity by combining the numbers from 0 to 9. In this case, it is easy to remember because of its simplicity, but it is considerably insecure compared to the password method that can combine alphabets and special characters.

Cards and IDs are used when the authentication requires the physical presence of the person and when the company is required to record the commute. In this case, one disadvantage is the difficulty in authentication if the card or ID card is lost.

To overcome these problems, biometric-information-based personal authentication is applied [8]. In the case of personal authentication using biometric information, information on different bodies is extracted for each individual; subsequently, the information is applied to the authentication process.

Because the characteristics of the body constitute one password, the risk of being changed or lost does not exist. Further, memorization is not required. This convenience enables a secure system to be built in many fields. In the case of biometric information used for biometric-authentication-based personal authentication, two main methods exist: behavioral characteristics and physical characteristics. The method to authenticate based on behavioral characteristics uses the method of gait, voice, and keying habits of people. [9]

Physical features include fingerprint authentication and face authentication, which are widely used in smartphones, and authentication methods using vein or ear forms are being studied. In such authentication method, an individual is authenticated by the external physical characteristics such as the distance between the eyes, the vein distribution, and the bending of the fingerprint as one feature point.

Physiological indicators such as electrocardiogram, blood pressure, pulse wave, and body temperature are also used. Personal authentication using electrocardiogram is one of the most actively studied areas of bio-signal-based research [10]. Smart watches using this technology is being studied and is expected to be used in various fields in the future [11].

However, in the case of biometric authentication, a problem occurs in each method. It was reported that iris recognition was impossible using complex iris patterns at the time of development, such that cloning and hacking could be prevented. However, the security of iris-based authentication became a hot topic when the German hacker group, "Chaos Computer Club" managed to hack iris recognition, as shown on YouTube [12].

In addition, a case has been reported where an individual was authenticated by another person after copying the fingerprint using gelatin. The abovementioned voice-based authentication method has a disadvantage in that it is significantly affected by the ambient noise. Therefore, a new identification method is required as an alternative.

2.2. Types of Bio-signals

The data used in biometric information authentication primarily uses bio-signals. Biological signals are electrical signals that are continuously measured from an organism [13]. Electrical signals are generated by the potential differences from tissues, cells, and organs associated with the nervous system.

Electrocardiography (ECG), electroencephalography (EEG), electrooculogram (EOG), and galvanic skin response (GSR) electromyography (EMG) are examples of biomedical signals. They can be obtained by attaching an electrode to a body part to obtain data [14]. Vital signs can be measured using several methods. In most cases, however, the measurement method is simple and uses a surface attachment method with no injury risk.

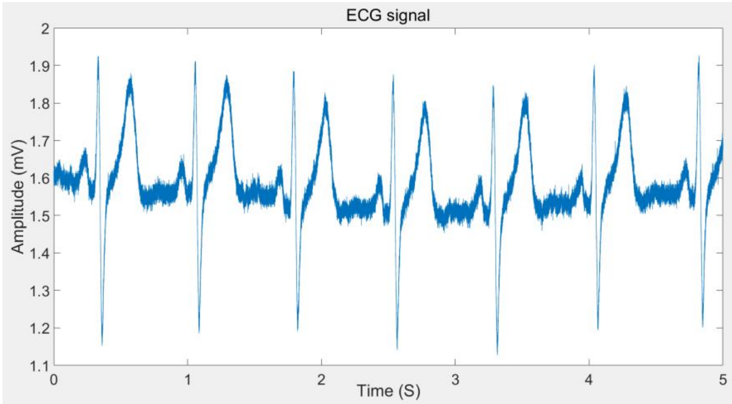
In this method, a Ag/AgCl wet electrode or a dry electrode is attached to the site where the bio-signal is measured, and then the bio-signal data is acquired. It is primarily used to acquire electrocardiogram, EMG, and brain wave data. The electrodes used to acquire biological signals are divided into ground electrodes and active electrodes depending on their roles.

The ground electrode sets the zero potential of the electrical signal. Therefore, it is attached to the earlobe or the back of the hand where electrical signals are hardly generated. The active electrode, meanwhile, receives the electrical signal at the location where the electrode is attached.

If the ground electrode is set to 0 V, the active electrode can detect the potential of the signal measurement site. Therefore, this electrode is attached to the position where biological signals such as brain waves, electrocardiogram, and EMG are to be measured. The abovementioned surface attachment method uses either the unipolar method or the dipole method [15]. In the unipolar method, a potential difference between the ground electrode and the active electrode is compared to acquire a living body signal.

Although an advantage occurs in that the bio-signal of the measurement site can be acquired as it is, one disadvantage is that it accepts the noise signal as it is. Meanwhile, in the dipole method, a living body signal is acquired by comparing the potential difference between the active electrodes. When the signal is input to the active electrode, the same component is minimized and only the different signal is amplified [16]. However, one drawback is that part of the biological signal is damaged.

2.2.1 Electrocardiography (ECG)



<Figure 2.1. ECG wave>

Electrocardiography is a graphical representation of the currents that occur in the myocardium according to the heartbeat. It is primarily used for the diagnosis of circulatory diseases [17]. ECG measurements are accurate, simple, and repeatable. It also has the advantage of low inspection cost.

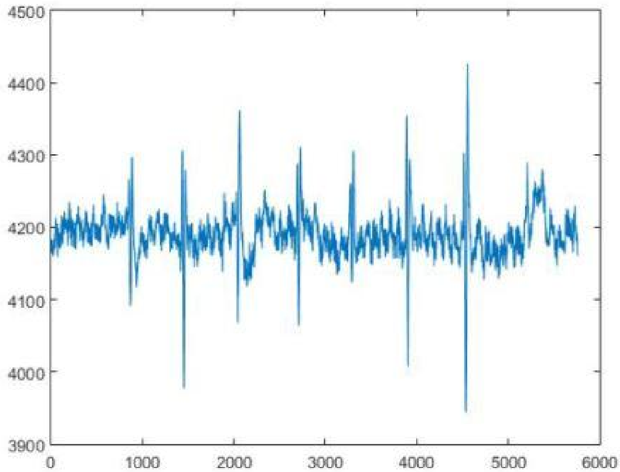
Electrocardiogram (ECG) is a 12-lead electrocardiogram (ECG) that acquires electrocardiogram data by attaching a wet electrode to a patient and a Holter test method periodically measures ECG in daily life [18, 19].

Additionally, the exercise electrocardiogram measures the electrocardiogram by applying a load to the heart through exercise. In hospitals, 12-lead electrocardiograms, which have the highest accuracy, are used primarily because they minimize movements.

The electrocardiogram signal has a certain form such as PQRST. It is associated with the contraction and relaxation of the heart and is affected by the heart's health and the degree of myocardial development. Therefore, each person has different types of ECG waveforms.

In biometric authentication, an individual is authenticated using this feature. We primarily analyze the size of the ECG waveform, the distance between the P wave and QRS wave, and the average frequency magnitude [20, 21].

2.2.2 Electroencephalography (EEG)



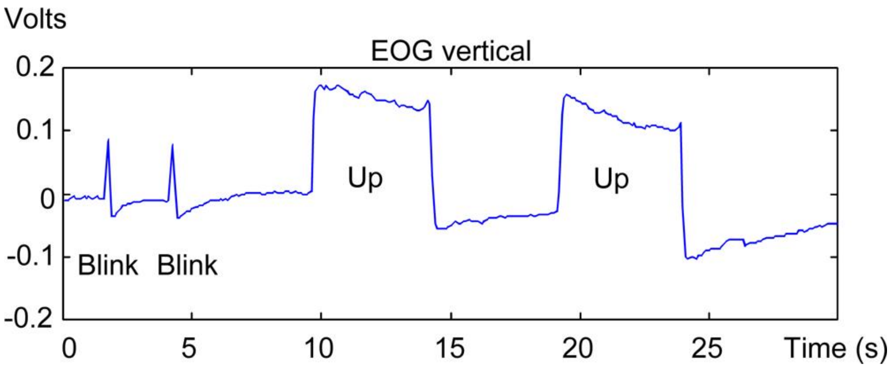
<Figure 2.2. EEG wave>

Electroencephalography is a graphical representation of the currents produced by brain activity. Depending on the brain activity, delta waves, theta waves, alpha waves, beta waves, or gamma waves may occur. By observing each waveform, not only the health condition of the brain but also the sleep quality can be determined.

EEG is transformed by thought and emotion [22]. Personal authentication can be performed using these characteristics. If one remembers the pre-designated password in one's head, EEG is detected and analyzed to proceed with the personal authentication.

For example, we extracted feature points such as the size of the delta wave in the brain and the frequency band of the gamma wave. At this time, the EEG compares and authenticates whether the EEG is that of the original registered user or the EEG of another person [23].

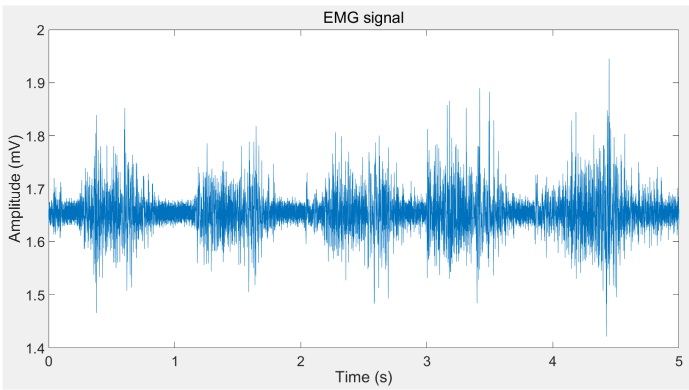
2.2.3 Electrooculogram (EOG)



<Figure 2.3. EOG wave>

Electrooculogram (EOG) is a graph of the eyeball's electrical movement [24]. A potential exists between the cornea side (positive, (+)) and the scleral side (negative, (-)) with the retina in between. When the eyeballs are facing the front, a potential difference does not exist. However, when the eyeball rotates vertically and horizontally, the direction in which the cornea moves is positive (+) and the opposite direction is negative (-), and then the potential difference is amplified and recorded.

2.2.4 Electromyography (EMG)



<Figure 2.4. EMG wave>

EMG is a graph of electrical signals generated in μV size inside the muscle when the body moves. At the beginning of electromyography research, it was primarily used to judge the health condition of the measurement site [25]. To determine the presence or absence of nerve abnormalities, a needle-shaped electrode is first inserted into the measurement site.

After the electrical stimulation was applied through the electrode, the response to the electrical signal was observed and the response of the nerve was noted. In addition to the needle electrode, a wet electrode is attached to analyze the EMG signal to identify the symptoms of muscle weakness and strength.

EMG signals have different characteristics, such as signal size, output shape, and frequency components, depending on the individual and body movements, even if measured at the same site.

This is because each person has different physical conditions, muscle mass, and strength. With this feature, computers can recognize human patterns. A controller called MYO exists in the market, and is used as an interface or a controller [26]. It can be used to translate sign languages or to correct postures because it can grasp hand movements.

2.3. Machine learning

Machine learning is a field in which algorithms and techniques are developed to help a computer learn. In general, machine learning is used to classify newly entered data after the computer learns the trend by using the training data. The advantage of applying machine learning is that if the computer learns the trend sufficiently well by using the training data, accurate outcome values can be derived [27].

Currently, research on the application of machine learning to voice recognition, disease diagnosis, image recognition, and other fields is being conducted. Self-driving cars based on machine learning have been developed till the commercialization stage. An important aspect of machine learning is the system learning process. Primarily, three methods of learning exist: supervised learning, unsupervised learning, and strengthening learning.

Supervised learning is a method to provide a computer with questions and their answers and then obtain the answers to new questions based on the training data [28]. The results and answers output by the system are compared and learned. This is done to reduce error and minimize the difference between the two products. At this point, the more the data learned from a system, the better the outcome of the map study. Typical examples of supervised learning include the SVM and KNN algorithms.

In contrast, a system employing unsupervised learning learns without data regarding the target [29]. The given data are analyzed and special points are extracted to find the answer from the specified data. An example of unsupervised learning is clustering, in which groups of data with similar characteristics are created.

The third method of learning is reinforcement learning, also known as strengthening learning. Reinforcement learning is typically used when an optimal behavior needs to be learned through interactions such as object control or a game [30]. It is a method to determine the best action in the current state. When executing an action, rewards are given in the external environment, where learning proceeds in a direction that results in the largest reward. In other words, strengthening learning is a learning method that functions using a feedback called “reward for results.”

2.4. Neural network theory

When the sensory organs of a living organism receive certain information, the information is sent to the brain through neurons. The brain processes this information by compiling it and subsequently commands it again. At this point, the neurons perform complex computations.

Artificial neural networks have been implemented in programming by referring to this method of processing information. Artificial neural networks can solve problems by changing the combined strength of each node through learning.

The process of recognizing handwriting using artificial neural networks is as follows.

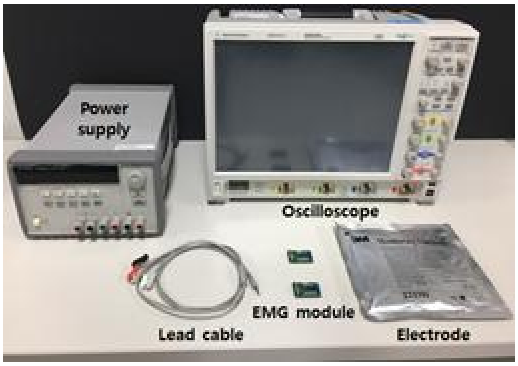
First, the pixel value of the image relative to the handwriting is entered into the computer. The weight is constantly transformed within the artificial neural network to obtain the proper output. This process continues till the last output neuron is activated. This ultimately determines which text has been read. Artificial neural networks typically consist of an input layer, hidden layer, and an output layer, and the overall configuration can be changed based on the requirements of the task.

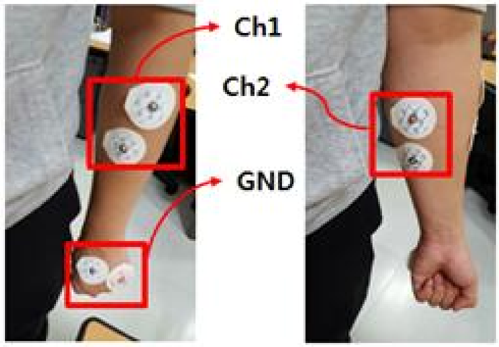
The most popular artificial neural network is the convolutional neural network (CNN). It applies artificial neural networks used for image recognition, in which images are divided into segments and special points are extracted, while strengthening their characteristics through filters [31]. The advantage is that it uses small learning parameters and renders learning easier than other neural networks, thereby accelerating data processing.

Another artificial neural network is the recurrent neural network (RNN). This neural network simultaneously calculates both the current input data and data received in the past [32]. The RNN has a memory capability because it is a structure that includes feedback. The memory ability facilitates in performing the work that general artificial neural network does not. A series of data, primarily images, can be recognized.

III. Method and Experiment

3.1 Data acquisition and experiment





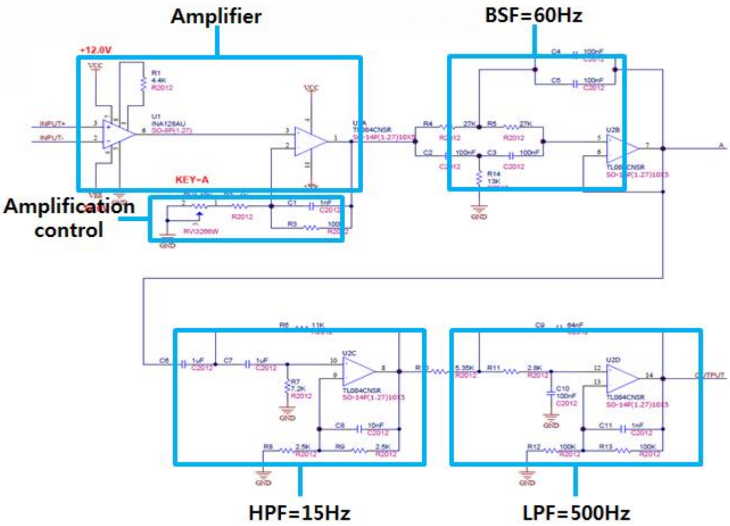
<Figure 3.1. EMG data acquisition environment (left), position of electrode (right)>

When a person moves, he or she uses a number of muscles simultaneously. Thus, a number of channels must be configured when obtaining the EMG data for a given movement. In this study, the EMG data were obtained from two channels.

The electrodes were used with three Ag/AgCl wet electrodes per channel. The active electrode that detects the EMG signal was attached on the back and front of the arm, approximately 10 cm from the elbow. Two active electrodes were used for each channel. The distance between two electrodes was 1 cm to prevent an overlap.

The ground electrode was attached to the back of the hand where no EMG signal was generated. The hand gesture was a strong repeated fist stroke. The elbow was subsequently fixed to the table to minimize the dynamic noise caused by the movement.

In total, 10 people participated in the experiment, and 10 sets of data were extracted per person. The experiment was performed using a self-produced EMG measurement module. The study on EMG-based personal authentication was conducted in two directions: the hardware part and the software part.

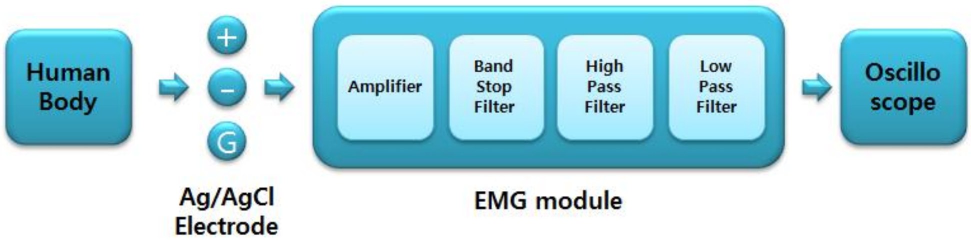


<Figure 3.2. EMG measurement circuit>

With regard to the hardware, EMG modules were designed that could measure the degree of EMG. The analog circuits of the EMG module were first designed using R and C and op-amps on the breadboard. The circuit was modified several times during this process.

The magnitude of the EMG signal is very small, ranging from μV to mV. In this case, the signal cannot be processed because of the directivity of the signal and noise. Therefore, the EMG signal is amplified 1000 times by using a differential amplifier.

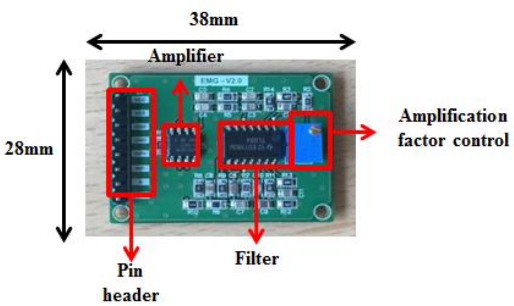
An analog circuit consists of a number of secondary Sallen–Key filters to eliminate noise signals present in the EMG signal. Sallen–Key filters are more efficient in filtering than primary filters because they possess radical filter characteristics. In addition, analog circuits can be simply constructed as they can be amplified while filtering signals.



<Figure 3.3. Data acquisition block diagram >

In general, the EMG signal exists in frequency band between 5 Hz and 450 Hz [33]. To detect signals in this band, the band pass filter, high pass filter, and low pass filter were configured using the Sallen–Key method. Because EMG signals differ between individuals it is difficult to obtain optimum results every time, even in the same environment.

For example, many factors such as body fat, muscle mass, and skin impedance vary between individuals. In this case, even if the same familiarity measurement module is used, a person may output a clear intensity signal, but another person may output a relatively smaller magnitude of one. Therefore, an EMG measurement environment that is suitable for the situation is required.



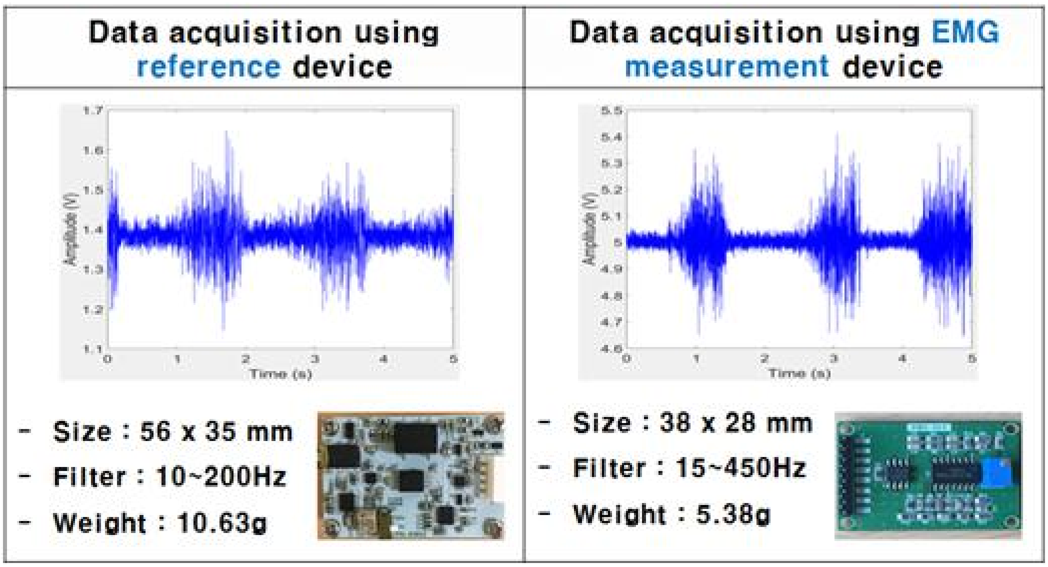
Classification	Contents
Size	38 mm x 28 mm
Power	-5 to 5 V (Double)
Filter (Low/High/Notch)	15 Hz / 450 Hz / 60 Hz
Wearing Area	Forearm
Weight	5.38 g

<Figure 3.4. EMG Module (left), specifications of EMG module (right)>

Hence, an electromyogram signal amplification rate control terminal was included in the analog circuit. The control terminals were fabricated using variable resistances and may be operated arbitrarily if a change in the amplification rate is required. The analog circuits that are designed around the Sallen–Key filter and the complete EMG modules was manufactured in 38 mm ´ 28 mm and used a positive source (-5 V to 5 V).

A pin header and a lead cable were used to enter the EMG data. The EMG signal was measured using this module and the data obtained can be seen in Figure 5. The graphs shown in Figure 5 show the EMG data measured when the fist was closed tightly. The performance of the two modules was compared using this EMG data.

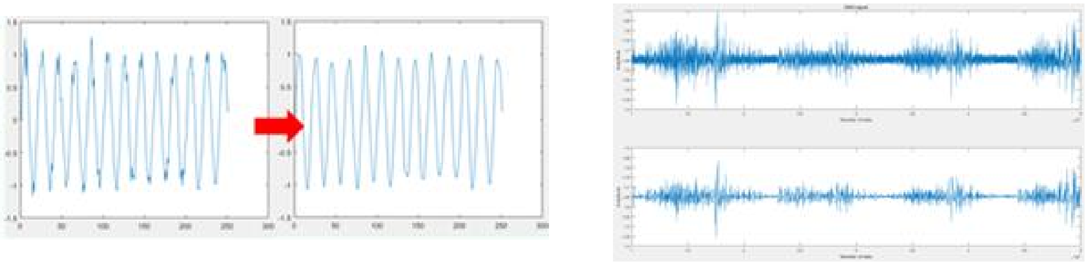
We confirmed that the fundamental noise in the results of the EMG measurement module decreased, compared to the reference module on the left. The EMG measurement module is approximately 50 % lighter than reference module.



<Figure 3.5. Reference Module (left), EMG Module (right)>

3.2 Electromyography (EMG) signal processing

The EMG signal includes noise caused by various factors such as cable movement and interference within the circuit. Such noise causes a decrease in the personal authentication rate. Therefore, filters were designed and applied using Matlab (2016a) to minimize the noise.

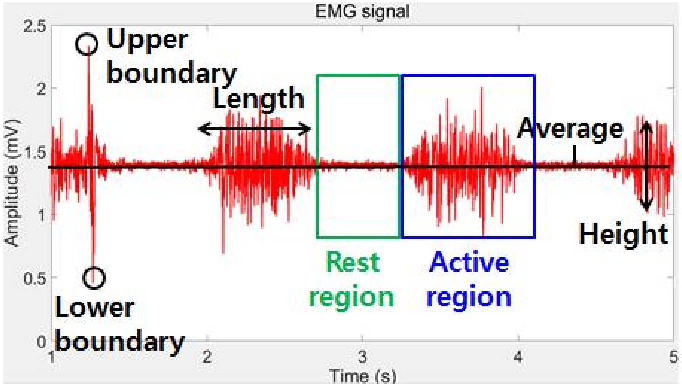


<Figure 3.6. Verification of digital filter performance (left), filtering of EMG signals (right)>

For filtering purposes, a high pass filter (0.5 Hz), low pass filter (200 Hz), and notch filter (60 Hz) were designed. The graphs in Figure 6 show the results of the performance verification of the designed filters. A sine wave with a specific frequency included noise at each interval, creating an irregular signal.

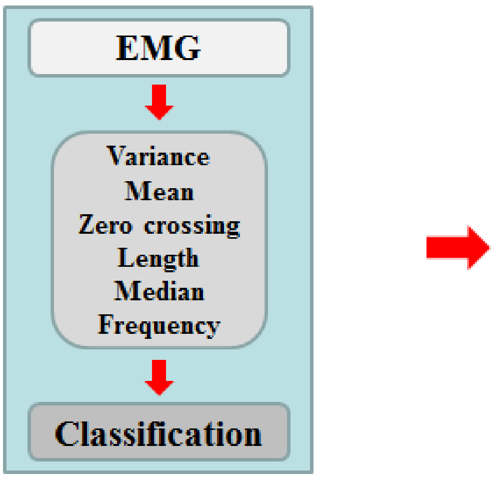
Subsequently, the designed filters were applied to the irregular signals to confirm that the sine wave characteristics were relatively improved. The aforementioned filters were applied to the EMG data. The graph on the right is an EMG signal. It can be seen that the filter reduces the noise.

3.3 Feature extraction for authentication



<Figure 3.7. Feature point of EMG signal>

A number of special precautions can be extracted from the EMG signal. Parameters such as the length, average, and maximum value of a signal can be used as special points (n is the number of data (length) and S is the full range of the signal). Several types of parameters have been extracted from the EMG signal for the EMG-based personal authentication.



Var	Mean	Zero Crossing	Signal Length	MedFreq
2.79E-03	3.88E-02	18748	396768	4.65E-01
2.86E-03	4.05E-02	16080	345095	4.00E-01
1.12E-03	2.73E-02	16454	365766	2.83E-01
2.30E-03	3.52E-02	14466	397984	3.77E-01
2.24E-03	3.26E-02	11578	406769	4.61E-01
2.43E-03	3.38E-02	12680	376130	4.93E-01
1.78E-03	3.06E-02	12314	439888	3.69E-01
3.10E-03	3.96E-02	13444	461550	4.32E-01
3.24E-03	3.82E-02	10888	487562	4.66E-01
2.51E-03	3.58E-02	12516	449266	4.17E-01
2.47E-03	3.36E-02	10614	438604	4.41E-01
2.71E-03	3.39E-02	11894	449010	5.46E-01
3.17E-03	3.78E-02	10378	454328	4.41E-01
2.97E-03	3.52E-02	11012	462306	4.94E-01
4.15E-03	4.36E-02	9646	423758	4.37E-01
3.21E-03	3.85E-02	12128	497563	4.34E-01
1.85E-03	3.11E-02	12278	409709	3.88E-01
2.25E-03	3.05E-02	9756	463023	5.01E-01
2.92E-03	3.30E-02	10470	375819	5.18E-01
2.14E-03	3.19E-02	11928	322122	3.77E-01
3.06E-03	3.59E-02	12242	444370	5.04E-01
2.98E-03	3.09E-02	8256	477394	6.66E-01
2.47E-03	3.08E-02	9788	209446	5.10E-01
2.05E-03	2.66E-02	10404	168903	5.59E-01
2.01E-03	3.00E-02	12454	291326	4.01E-01
1.93E-03	2.58E-02	10866	166900	6.01E-01
1.99E-03	2.90E-02	12644	201993	4.39E-01
1.75E-03	2.71E-02	11346	184174	4.79E-01

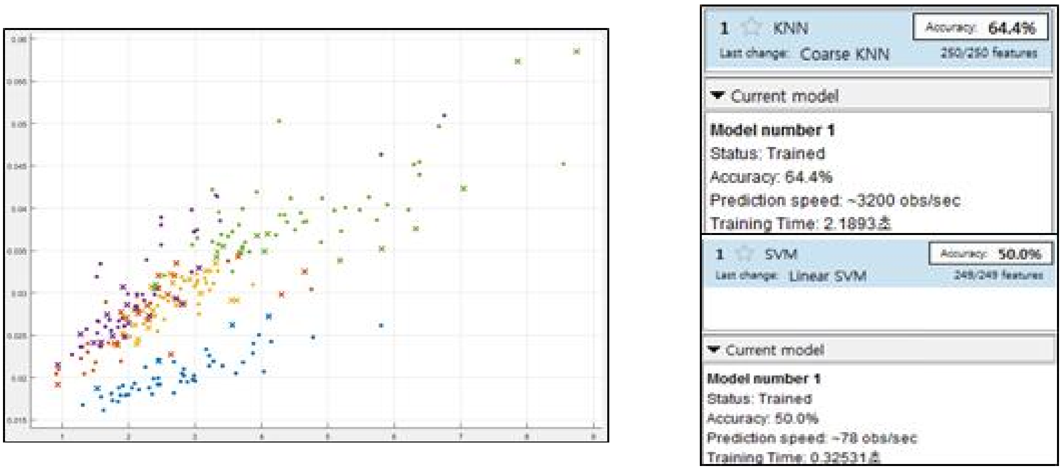
<Figure 3.8. Feature extraction in EMG signal>

In this study, we extracted five parameters from the EMG signal, including the variance, mean, zero crossing value, length, and median frequency. In addition, the average amplitude change (AAC), log detector (LOD), mean absolute value (MAV), root mean square (RMS), and waveform length (WL) were extracted.

$$(1)EMG_S = \sqrt{\frac{1}{N}\sum_{N=1}^{N}|EMG_n|^2} \qquad (2)\,EMG_{\log} = \exp^{\frac{\sum_{N=1}^{N}\log|s|}{N}}$$

< Equation 1. EMG parameter calculation equation >

However, to improve the EMG-based personal authentication rate, non-overlapping parameters were selected and applied to the personal authentication.



<Figure 3.9. EMG data distribution (left), SVM- and KNN-based personal authentication results (right)>

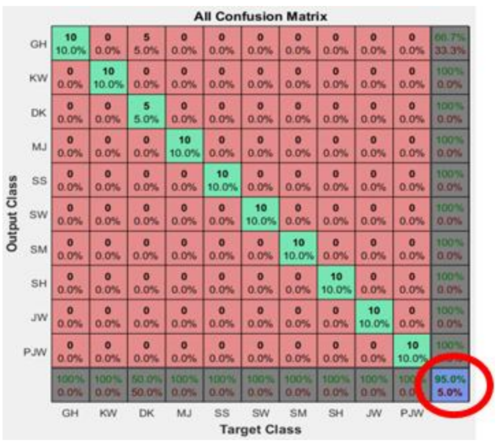
3.4 Person classification using machine learning

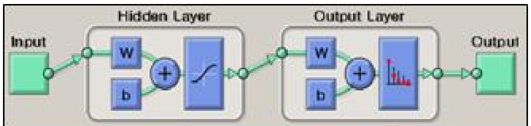
The graph in Figure 8 shows the distribution of the EMG data of five persons, i.e., 50 per person. The KNN and SVM algorithms were used to classify the EMG data [34]. The KNN algorithm compares “K” data based on randomly specified reference points.

It also classifies the targets into categories that correspond to the largest number of data. The KNN algorithm was applied to classify the EMG data, which resulted in 64.4 % (161/250) of the personal certification results. The next machine-learning technique that was applied is the SVM algorithm.

First, the segments are divided by the data. Subsequently, the newly entered EMG data is classified into the zone category. Applying the SVM algorithm to classify the EMG data yielded 50.0 % (125/250) for the personal certification results.

The results of individual certification using KNN and SVM algorithms are too low to be used for certification. Artificial neural networks were used to improve the individual certification rates.





	Number of data	Percentage
Training data	80	80%
Test data	10	10%
Validation data	10	10%
Total	100	100%

<Figure 3.10. EMG-based personal authentication result >

An artificial neural network was applied to distinguish the extracted feature points [35].

The structure of the artificial neural network used in this study consists of the input layer, hidden layer, and output layer. When the EMG data are provided to the input layer, the hidden layer matches the feature points. The results of the aforementioned process are passed to the output layer. An artificial neural network with this structure is called a feedforward neural network.

The feedforward neural network uses a map-learning method to determine and train the output value of the data. When the EMG data are provided to the input layer, the bias is determined based on the weight present in the hidden layer. Subsequently, the operation value is transferred to the next hidden layer. In the final output layer, the error between the desired output value and the actual output value is calculated. Subsequently, the method of correcting the weight and bias is re-learned by transmitting the difference as the error value in the direction of the input layer.

IV. Conclusion

We conducted a study to certify individuals using EMG. The EMG signal is an electrical signal generated by movements and can be easily measured by the surface attachment method. EMG signals are not affected by the weather, ambient brightness, and noise. Further, because one does not have to remember the signal like a password, one does not have to worry about losing it. Therefore, the EMG signal can be conveniently used for personal authentications. For an EMG-based personal authentication, we studied two aspects, hardware and software.

In the hardware case, a low-noise EMG measurement module was fabricated. The EMG measurement module was designed to improve the EMG-based personal authentication rate. The header pin is used to voltage -5 and 5, and the EMG signal is input or output through the header pin.

In the case of analog circuits designed inside the module, a Sallen–Key-type high pass filter, low pass filter, and band stop filter are configured. Further, an amplification rate control terminal was used for acquiring the optimum electromyogram signal depending on the situation. The EMG measurement module was fabricated with dimensions of 38 mm ′ 28 mm, such that it may be incorporated in bio-signal measurement devices through continuous development. It is 35 % smaller than the conventional EMG measurement module (reference module). Further, its weight is 50 % lighter, i.e., from 10.63 g to 5.35 g.

It was found that more accurate EMG data could be acquired by using the proposed EMG module as compared to the conventional EMG module.

Regarding software, an individual was authenticated using an artificial neural network. Many parameters were extracted from the EMG signals using Matlab code. The parameters were extracted from five variables: variance, mean, zero crossing value, length, and median frequency. The extracted parameters were classified by the feedforward neural network. Ten electromyogram parameters were classified with an accuracy of 95.0 %.

Reference

[1] Varsha J. Rathod, Nalini C. Iyer, et al, "A survey on fingerprint biometric recognition system", Green Computing and Internet of Things (ICGCIoT), 2015 International Conference on, pp. 323-326, Oct.2015.

[2] Sarika B. Solanke, Ratnadeep R. Deshmukh, "Biometrics — Iris recognition system" A study of promising approaches for secured authentication, Computing for Sustainable Global Development (INDIACom), 2016 3rd International Conference on , pp.811-814, March 2016.

[3] Ryszard S. Choras, "Personal identification using ocular vein biometric", Industrial Electronics and Applications (ICIEA), 2017 12th IEEE Conference on, pp. 195-200, June 2017.

[4] Juhi Malhotra, Netra Raina, "Biometric face recognition and issues", Computing for Sustainable Global Development (INDIACom), 2015 2nd International Conference on, pp. 1239 – 1241, March 2015.

[5] News Market Analysis, "Global biometrics market to increase from $2bn in 2015 to $14.9bn by 2024", Biometric Technology Today, Vol 6, pp. 1 – 12, Jun 2015.

[6] Emanuela Marasco, Carlo Sansone, "An anti-spoofing technique using multiple textural features in fingerprint scanners", Biometric Measurements and Systems for Security and Medical Applications (BIOMS), 2010 IEEE Workshop on, pp. 8 - 14, Sep 2010.

[7] Yogaratnam Nagaratnam, Wai Kit Wong, "Miniature Digital Pin-Number Lock", 2010 Second International Conference on Computer Research and Development , pp. 686 - 691, May 2010.

[8] Ahmed Mahfouz, Tarek M. Mahmoud, Ahmed Sharaf Eldin, "A survey on behavioral biometric authentication on smartphones", Journal of Information Security and Applications, Vol 37, pp. 28 - 37, Dec 2017.

[9] Miran Lee, Jaehwan Ryu, Inchan Youn, "Biometric personal identification based on gait analysis using surface EMG signals", 2017 2nd IEEE International Conference on Computational Intelligence and Applications (ICCIA) , pp 318 - 321, Sep 2017.

[10] Ruggero Donida Labati, Enrique Muñoz, Vincenzo Piuri, Roberto Sassi, Fabio Scotti, "Deep-ECG: Convolutional Neural Networks for ECG biometric recognition", Pattern

Recognition Letters, Available online 28 March 2018.

[11] Yung-Chieh Lin, Kai-Che Wei, "An electronic smart watch monitors heart rate of an extremely preterm baby", Pediatrics & Neonatology, Vol 59, pp. 214 - 215, Apr 2018

[12] See : https://www.youtube.com/watch?v=w3Yexpw6k3w

[13] See : https://en.wikipedia.org/wiki/Biosignal

[14] Ning Ji, Yanbing Jiang, Zijian Yang, Xiaobei Jing, Hui Wang, Yue Zheng, "An active electrode design for weak biosignal measurements", 2016 IEEE 13th International Conference on Signal Processing (ICSP), pp. 502 - 507, Mar 2016.

[15] Odrika Iqbal, Shaikh Anowarul Fattah, Saima Zahin, "Hand movement recognition based on singular value decomposition of surface EMG signal", 2017 IEEE Region 10 Humanitarian Technology Conference (R10-HTC), pp. 837 - 842, Dec 2017.

[16] See : https://www.wikilectures.eu/w/Unipolar_and_bipolar_connection.

[17] Wenhan Liu, Qijun Huang, Sheng Chang, Hao Wang, Jin He, "Multiple-feature-branch convolutional neural network for myocardial infarction diagnosis using electrocardiogram", Biomedical Signal Processing and Control, Vol 45, pp 22 - 32, Aug 2018.

[18] Petros Arsenos, Konstantinos A. Gatzoulis, Polychronis Dilaveris, Skevos Sideris, Dimitrios, "T wave alternans extracted from 30-minute short resting Holter ECG recordings predicts mortality in heart failure", Journal of Electrocardiology, Vol 51, pp 588 - 591, Aug 2018.

[19] Hubert V. Pipberger, Stanley M. Bialek, Joseph K. Perloff, Harold W. Schnaper, "Correlation of clinical information in the standard 12-lead ECG and in a corrected orthogonal 3-lead ECG", American Heart Journal, Vol 61, pp 34 - 43, Jan 1961.

[20] Abdelkader Sellami, Amine Zouaghi, Abdelhamid Daamouche, "ECG as a biometric for individual's identification", Electrical Engineering - Boumerdes (ICEE-B), 2017 5th International Conference on, pp.1-6, Oct. 2017.

[21] Mario Merone, Paolo Soda, Mario Sansone, Carlo Sansone, "ECG databases for biometric systems: A systematic review", Expert Systems with Applications, Vol. 67, pp. 189-202, Jan 2017.

[22] Debashis Das Chakladar, Sanjay Chakraborty, "EEG based emotion classification using "Correlation Based Subset Selection" ", Biologically Inspired Cognitive Architectures, Vol 24, pp. 98 - 106, Apr 2018.

[23] Emanuele Maiorana, Daria La Rocca, Patrizio Campisi, "Eigenbrains and Eigentensorbrains: Parsimonious bases for EEG biometrics", Neurocomputing, Vol 171, pp. 638-648, Jan 2016.

[24] Hande Erkaymaz, Mahmut Ozer, İlhami Muharrem Orak, "Detection of directional eye movements based on the electrooculogram signals through an artificial neural network", Chaos, Solitons & Fractals, Vol 77, pp. 225 - 229, Aug 2015.

[25] Yikun Gu, Dapeng Yang, Qi Huang, Wei Yang, Hong Liu, "Robust EMG pattern recognition in the presence of confounding factors: features, classifiers and adaptive learning", Vol 96, pp. 208-217, April 2018.

[26] See : https://www.thalmic.com/

[27] Yong Penga, Wanzeng Kong, Bing Yang,", Orthogonal extreme learning machine for image classification", Neurocomputing, Vol 266, pp. 458-464, November 2017.

[28] Mohamed El Mohadab, Belaid Bouikhalene, Said Safi, "Predicting rank for scientific research papers using supervised learning", Applied Computing and Informatics, March 2018.

[29] Ezequiel López-Rubio, Esteban J. Palomo, Francisco Ortega-Zamorano, "Unsupervised learning by cluster quality optimization", Vol 436–437, pp. 31-55, April 2018.

[30] Isshu Munemasa, Yuta Tomomatsu, Kunioki Hayashi, Tomohiro Takagi, "Deep reinforcement learning for recommender systems", Information and Communications Technology (ICOIACT), 2018 International Conference on , pp.226 - 233, April 2018.

[31] Wenzhu Yang, Qing Liu, Sile Wang, Zhenchao Cui, Xiangyang Chen, Liping Chen, Ningyu Zhang, "Down image recognition based on deep convolutional neural network", Information Processing in Agriculture, vol 5, pp.246-252, June 2018.

[32] Jônatas Wehrmann, Gabriel S. Simões, Rodrigo C. Barrosa, Victor F. Cavalcante, "Adult content detection in videos with convolutional and recurrent neural networks", Neurocomputing, Vol 272, pp 432-438, January 2018.

[33] Ömer Özkan, Hilmi Uysal, Övünç Polat, Ömer Halil Çolak , "Investigation of active channels in multi-channel surface arm EMG recordings for 24 different movements ", Biomedical Engineering Meeting (BIYOMUT) 2014 18th National, pp. 1 -4, Jan 2015.

[34] Karaputugala Madushan Thilina, Kae Won Choi, Nazmus Saquib, Ekram, "Pattern classification techniques for cooperative spectrum sensing in cognitive radio networks: SVM

and W-KNN approaches", 2012 IEEE Global Communications Conference (GLOBECOM) , pp. 1260 - 1265, Dec 2012.

[35] Suchin Adhan, Chuchart Pintavirooj, "Thai sign language recognition by using geometric invariant feature and ANN classification", 2016 9th Biomedical Engineering International Conference (BMEiCON), pp. 1 - 4, Dec 2016.

List of Publications

Paper

1) Jaehyo Jung, Jihoon Lee, **Si Ho Shin** and Youn Tae Kim, "Development of a Telemetric, Miniaturized Electrochemical Amperometric Analyzer", Sensors, 17(10), 2416-2424 (2017)

2) **Si Ho Shin,** Jaehyo Jung, Jihoon Lee and Youn Tae Kim, "An improved EMG-based authentication method for wearable devices", International Journal of Intelligent Automation & Soft Computing will be submitted June 10, 2018

List of Publications

Conference

1) **Si Ho Shin,** Seokeun Park, Jaehyo Jung and Youn Tae Kim, "Gesture-based controller using wrist electromyography and a neural network classifier", Biomedical Engineering and Sciences (BIOENG'16), Jul. 2016.

2) Jaehyo Jung, **Si Ho Shin** and Youn Tae Kim, "Flexible Dry Electrodes Made from CNT/Textile Composite for ECG Sensor", Biomedical Engineering and Sciences (BIOENG'16), Biomedical Engineering and Sciences (BIOENG'16), Jul. 2016.

3) **Si Ho Shin,** Jaehyo Jung and Youn Tae Kim, "A study of an EMG-based authentication algorithm using an Artificial Neural Network", sensors, Proceedings of the IEEE Conference on Sensors, Nov. 2017

List of Publications

Patent

1) Youn Tae Kim, Jaehyo Jung, **Si Ho Shin**, “wearable device for measuring edema index and method of measuring edema index using same”, Nov. 30.2016, US 15/364,326

2) Youn Tae Kim, Jaehyo Jung, **Si Ho Shin,** “APPARATUS AND METHOD OF MONITORING BIO SIGNAL OF BICYCLIST AND COMPUTER READABLE MEDIUM”, US 15/871,334

3) Youn Tae Kim, Jaehyo Jung, **Si Ho Shin,** "Carbon Nanotune Composite Electrode Using Vacuum Suction", US 15/129840

4) Youn Tae Kim, Jaehyo Jung, Ji hun Lee, **Si Ho Shin,** "Sensor for measuring Biometric Information and Item of Clothing Including the Same", US 9/79539

5) Youn Tae Kim, Jaehyo Jung, Ji hun Lee, **Si Ho Shin,** "생체 정보 측정 센서 및 이를 포함하는 의류", 10-1797907

6) Youn Tae Kim, Jaehyo Jung, **Si Ho Shin,** "부종 지수의 측정을 위한 웨어러블 디바이스 및 이를 활용한 부종 지수 측정 방법", 10-1823496

7) Youn Tae Kim, Jaehyo Jung, **Si Ho Shin,** "진공 흡착을 이용한 CNT 혼합 전극", 10-2017-0129840