A Study on EMG-based Biometrics

Jin Su Kim and Sung Bum Pan*
Chosun University, Dong-gu, Gwangju, 61452, Korea
babotn5@gmail.com, sbpan@chosun.ac.kr

Abstract

Biometrics is a technology that recognizes user's information by using unique physical features of his or her body such as face, fingerprint, and iris. It also uses behavioral features such as signature, electrocardiogram (ECG), electromyogram (EMG), and electroencephalogram (EEG). Among them, the EMG signal is a sign generated when the muscles move, which can be used in various fields such as motion recognition, personal identification, and disease diagnosis. In this paper, we analyze EMG-based biometrics and implement a motion recognition and personal identification system. The system extracted features using non-uniform filter bank and Waveform Length (WL), and reduced the dimension using Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). Afterward, it classified the features using Euclidean Distance (ED), Support Vector Machine (SVM), and K Nearest Neighbors (KNN). As a result of the motion recognition experiment, 95% of acquired EMG data and 84.66% of UCI data were obtained, and as a result of the personal recognition experiment, 85% of acquired EMG data and 88.66% of UCI data were obtained.

Keywords: Biometrics, Electromyogram, Personal Authentication

1 Introduction

In modern society, there are frequent needs to identify oneself. The conventional methods of identification include the knowledge-based Identifier (ID)/Password (PW) method and the ownership-based ID card method. However, while the former method involves inconvenience of remembering the ID/PW and the risk of PW leakage, the latter method has the risk of loss, theft, and counterfeiting as well as the inconvenience of having to carry an authentication device all the time. In order to eliminate the inconvenience and risks of existing methods, the need for biometrics is increasing [18].

Biometrics is a technology that recognizes user's information by using unique physical features of his or her body. It utilizes physical and behavioral features as shown in Fig 1. The physical ones include face, fingerprint, and iris, and the behavioral ones include signature, gait, ECG, EMG, and EEG [17]. Among them, the biometrics that is popular now recognizes such physical features as face, fingerprint and iris but, as they can be falsified and altered, they are used for various crimes as shown in Table 1.

To resolve these issues, studies on ECG recognition, EMG recognition, and EEG recognition using behavioral features have been started. The ECG is a signal measured in the form of voltage in relation to heartbeat, which can be used for personal identification and disease diagnosis, and the EEG is a signal that changes according to the activity of the cerebrum, which can be used for situation identification and personal identification. On the other hand, the EMG, which is an activity potential signal generated when muscle contracts, has a wide range of frequency band and voltage values from 5 to 10,000 Hz, and can be used for various applications such as personal identification, motion recognition, and disease diagnosis. In this paper, we analyze the trend of biometric systems using EMG, and conducts motion recognition and personal identification experiments.

Journal of Internet Services and Information Security (JISIS), volume: 7, number: 2 (May 2017), pp. 19-31
*Corresponding author: Department of Electronics Engineering, Chosun University, Dong-gu, Gwangju, 61452, Korea, Tel: +82-62-230-6897

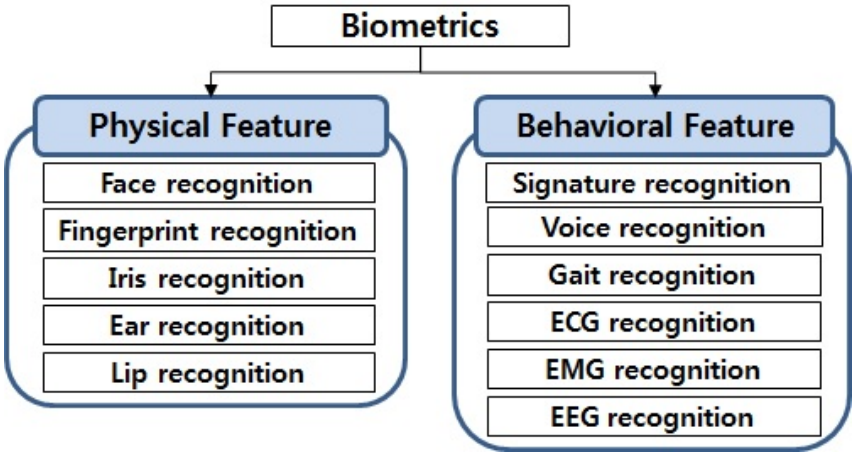


Figure 1: Types of biometrics

Table 1: Examples of crimes using physical features

Country	Details
USA	Hacking using live images of the registered user's face
Brazil	Passing through the entrance using fake silicon fingerprint
Korea	Financial accidents 3-D printed fake fingerprint
Japan	Electronic passports using fake fingerprint
Russia	Hacking using the iris reproduced from the president's photo

This paper is organized as follows: Section 2 describes previous studies about various recognition systems, applications, and public databases (DB) using EMG signals; Section 3 describes motion recognition and personal identification experiments using WL and non-uniform filter bank; Section 4 shows experimental results using sEMG basic hand movements upatras data of UCI and the acquired EMG signal data; and lastly Section 5 concludes this study.

2 Trends of EMG Recognition System

The EMG signal is an electric signal generated when muscle contracts, which can be used in various fields and for which a variety of studies have been conducted and various public DBs exist. As different muscle parts are measured according to the purpose of using the EMG signal, it is necessary to examine necessary technical matters and understand related DB in advance in order to proceed with the study.

2.1 EMG-based recognition system

The measured EMG signal includes various types of information such as muscle movement and muscle fatigue, and thus requires preprocessing depending on the purpose of use. It contains information about muscle movement in the low frequency band below 500Hz. To use this information, a band-pass filter or a low-pass filter is needed and to remove external power noise, a notch filter at 50Hz is used [4, 16]. Fig 2 shows the EMG signal waveform, in which (A) shows the measured EMG signals and (b) shows the EMG signals after preprocessing.

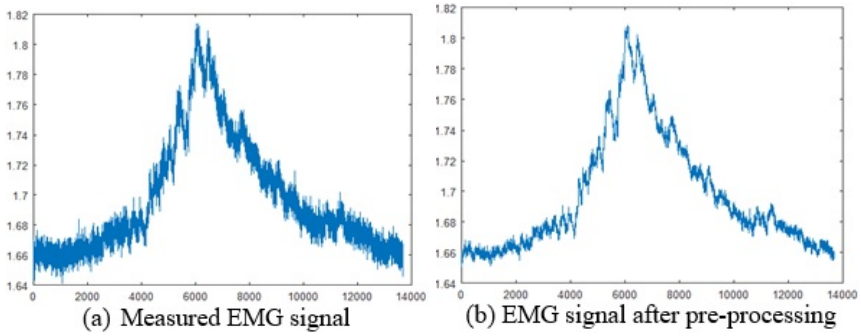


Figure 2: EMG signal waveform

The motion recognition systems using EMG signal operated as follows: The first method used a scaling function. It increased the processing speed for the 2-channel EMG signals measured at the biceps and shoulder triceps, by reducing the data size through sampling of a certain section. Then, it measured the average amplitude of the elbow motion at 0, 45, 90, and 125 degrees and that of the shoulder joint at 0, 45, 90, 135, and 180 degrees as shown in Fig 3, and then calculated a scaling factor using the scaling function [4].

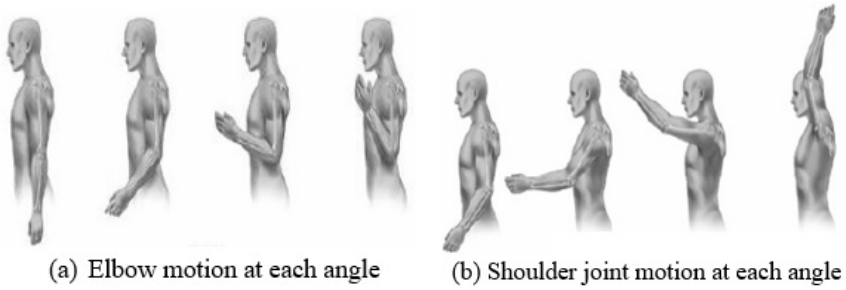


Figure 3: Motions measured to obtain the average amplitude

The second method used PCA. It used the EMG signals from two channels measured at the brachioradialis and at flexor carpi ulnaris, and extracted the features of the upper, lower, left, and right wrist signals using PCA. It indicated the recognition rate as a percentage of error counts by repeating each operation 30 times, and the average recognition rate of four motions of the wrist was 85% [16].

The third method used a total of seven features such as ZC, WL, MAV, SK, VAR, mobility and complexity. EMG signals represented nine finger movements with signals measured at two channels of brachioradialis and flexor carpi ulnaris of four person. For classifiers, it used KNN and Artificial Neural Network (ANN), and the finger motion recognition rate was 86% for KNN and 93% for ANN [8].

The fourth method used the average shift filter. The EMG signals were measured at 8 channels surrounding the muscles under the forearm of the right hand and the outline of the waveform was obtained using the average moving filter. Then, two thresholds points were set and the waveform outline is summarized as shown in Fig 4. The recognition rate was 92.3% in average [10].

The fifth method used a total of five features such as MAV, WL, RMS, SSI, and VAR. The EMG signals measured at four channels of femoral rectus femoris, vastus lateralis, vastus medialis, and semitendinous muscles of three person were used to classify the gait phases. As shown in Fig 5, the gait phases were classified into two phases, i.e., the stance phase and the swing phase. When LDA classifier was used, the average performance was 76% [23].

The sixth was a sign language recognition method that uses a total of 10 features: MAV, MMAV, SSI,

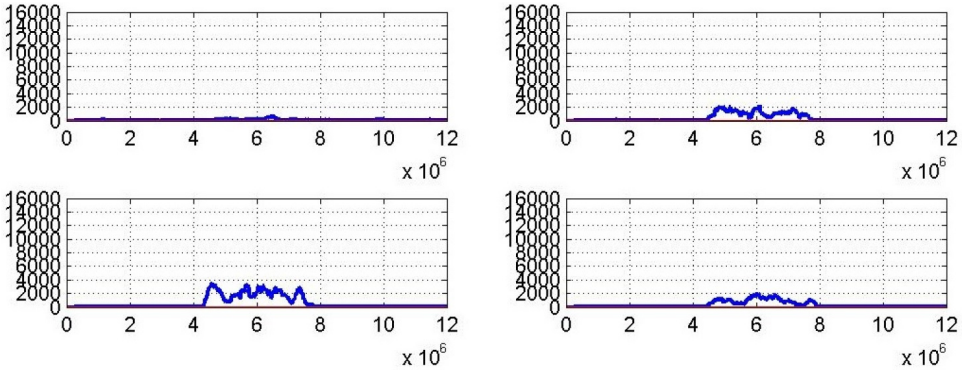


Figure 4: Waveform outline using thresholds values

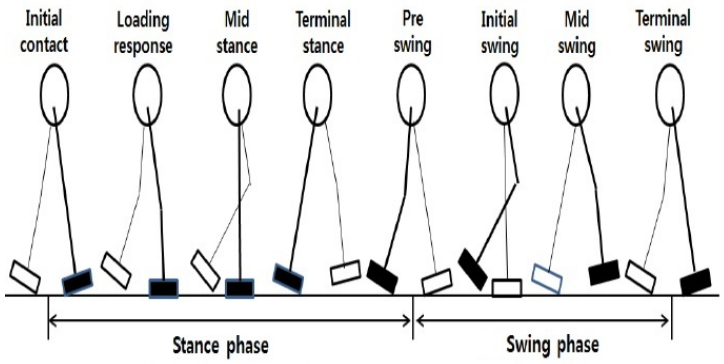


Figure 5: Human gait phases

RMS, log detector, AAC, MFL, maximum value, minimum value, and standard deviation. The EMG signal was measured at 8 channels on the subject's right arm and each motion was repeated 80 times. With the measured EMG signals, 26 sign language motions were recognized and as for the classifier, SVM's Radial Basis Function (RBF) was used. The performance of the offline system experiment was 91% while that of the real-time system experiment was 82.3% [22].

The following personal identification systems using the EMG signal were examined: The first method used a non-uniform filter bank as shown in Fig 6. Personal features were extracted by the non-uniform filter bank method using the EMG signals measured at two channels of the flexor carpi ulnaris and the wrist for 3 days. Then, the collected data was reduced through vector quantization modeling and then classified using Gaussian Mixture Modeling (GMM). Using the EMG signals of the hand, 49 person were identified and the recognition rate showed an average performance of 83.94% [15].

Figure 6: Flowchart for personal identification using a non-uniform filter bank

The second method used 12 time domain features (RMS, MAV, VAR, WAMP, ZC, SSC, IEMG, MMAV1, MMAV2, MAVSLP, SSI, and WL) as shown in Fig 7. The EMG signals measured at four channels such as femoral rectus femoris, vastus medialis, vastus lateralis, and semitendinosus muscles of 20 person were used. As for the classifier, ANN was used and users were identified using the EMG

signal of the gait. When all 12 features were used, the average identification rate was 99.7% and while it was 96% when only three muscles and five features were used [14].

Figure 7: Flowchart for personal identification using time domain features

2.2 Fields of application

EMG signals are more versatile than other bio-signals. As shown in Table 2, they can be used for games, medical fields, daily living, and robotics. Firstly, in the field of games, they are used to control certain actions in the game. Microsoft has applied for a patent for this, where EMG signals of the fingers are used to play a music game as shown in Fig 8(a) [3]. Another example is OBME game app on Android mobile phones, where the player in the game jumps when the EMG signal of the hand is measured as the person applies power to his or her hand, as shown in Fig 8(b) [6]. Fig 8(c) shows a type of rehabilitation therapy game that controls jumping through up and down movement of the arm [9].

Table 2: Application of EMG signals

Application	Description
Games	Control for various games such as FPS game, music game, and etc.
Medical	Wheelchair control, disease diagnosis, and etc.
Daily Living	Sign language recognition, smart-phone control, and home appliance control
Robotics	Strength improvement clothes, artificial robotic hands, etc.

(a) Microsoft music game (b) Android OBME game

(c) Rehabilitation therapy game

Figure 8: Games using EMG signals

Secondly, in the medical field, EMG signals are used for wheelchair control and disease diagnosis. Instead of the conventional method of controlling the wheelchair with a joystick, EMG signals are used to control the movement of the wheelchair by recognizing its certain patterns such as stopping, going

forward, and going backward [11]. In addition, it is also possible to diagnose diseases by obtaining various types of information about muscles, using muscle activity, muscle fatigue, and etc.

Thirdly, in the field of daily living, EMG signals are used to recognize sign languages as shown in [22], so that people who rely on sign language can communicate which those who do not know it. They can move or select the smart-phone screen only with EMG signals of their hand, without actually touching the phone. Fig 9 is a photograph of controlling a computer using a wireless EMG terminal. EMG signals can make it possible to conveniently control and use electronic devices like as mouse and computer [7].

Figure 9: Computer control using EMG signals

Lastly, in the robotics field, EMG signals are used to control the robotic device by wearing it or wirelessly. The strength enhancement suit is a device that enables the user to exercise stronger force than usual by using the EMG signal of his or her body. Artificial robotic hands are being studied for people who have lost their hand due to an accident. One can control his or her artificial hand at will, using the EMG signals measured at the sensors attached to his or her body.

2.3 Public databases

For EMG signals, different muscle data are used depending on the purpose of use. Therefore, it is necessary to understand database in order to properly use public databases. Table 3 lists the summary of public EMG signal databases. The first is UCI's EMG dataset in the Lower Limb Dataset. It was to observe the movement of muscles around the knee. It was established by recording EMG signals measured at four channels of rectus femoris, biceps femoris, vastus medialis, and semitendinosus muscle

Table 3: Public EMG DBs

Name	Description	Size of dataset	Content
EMG Dataset in Lower Limb Dataset	UCI	66	Observation of muscle movement around knees
sEMG Basic Hand Movements Upatras	UCI	900 ˜1,800	Observation of 6 movements of hands
EMG (Dr. Rami Khushaba)	Dr. Rami Khushaba	45 ˜600	Observation of finger movements
MIT-BIH Polysomnographic	Physionet	18	Diagnosis of apnea syndrome by observing the jaw movement
Stress Recognition in Automobile Drivers	Physionet	18	Stress while driving

for three movements of sitting, standing, and walking, of 11 normal person and 11 abnormal person.

The second is UCI's sEMG for Basic Hand movements Data Set. As shown in Fig 10, EMG signals were measured at the extensor carpi ulnaris and the flexor carpi ulnaris muscles of the hands of five person aged between 20 and 22, in order to recognize six motions of the hands. The data was preprocessed using a band pass filter and a notch filter, in total 2 sets. Set 1 consisted of 900 data obtained by measuring the five person hand motions, each repeated 30 times a day, and Set 2 consisted of 1,800 data obtained by measuring one person's hand motions, each repeated 100 times a day for three days [21, 20].

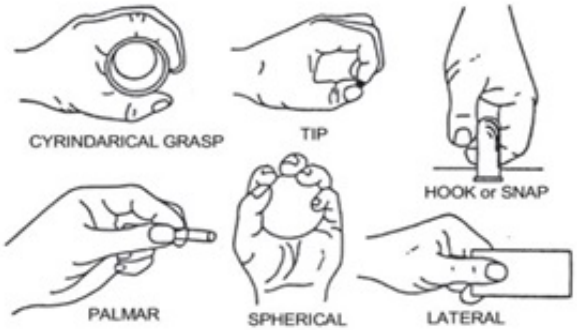
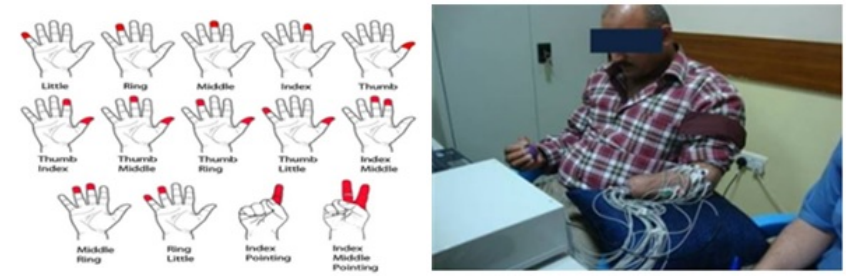


Figure 10: Six hand motions in sEMG for Basic Hand Movements Dataset

The third is Dr. Rami Khushaba's EMG data. It was processed using a band pass filter and a notch filter and then divided into 5 sets. As shown in Fig 11(a), Sets 1 to 3 were obtained by measuring 8 person finger movements at 2 channels and 8 channels of extensor carpi ulnaris, extensor carpi radial and extensor digitorum. Set 4 was the EMG signals measured at 8 channels on a person whose hand had been severed, as shown in Fig 11(b). Set 5 recorded data about the effects of muscle contraction, based on EMG signals measured at 6 channels [13].



(a) Combination of 14 finger movements (b) Record of EMG signals

Figure 11: Dr. Rami Khushaba' EMG data

The fourth dataset contains Physionet's MIT-BIH Polysomnographic data, which is used for evaluating chronic obstructive sleep apnea using various physiological signals such as ECG, EEG, and EMG obtained from 16 person aged 32 to 56 years. The last one is Physionet's Stress Recognition in Automobile Drivers. It is used for evaluating the driver's stress during driving, using various physiological signals such as ECG and EMG measured at the right hand trapezius.

3 Motion Recognition and Personal Identification System

As shown in Fig 12, the motion recognition and the personal identification experiment was conducted using EMG signals. From the EMG signals entered, features were extracted using the WL, which is a time domain feature extraction method, and the non-uniform filter bank, which is a frequency domain feature extraction method. The feature vector using the time domain and the frequency domain has an advantage of expressing the class distribution well [2]. Afterwards, PCA and LDA were performed to reduce the data size and the data was classified using ED, SVM, and KNN.

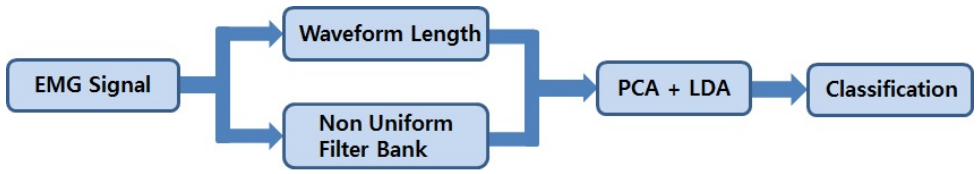


Figure 12: Flowchart for motion recognition and personal identification experiment

The time domain of the EMG signal expresses information about the activity of muscles, and there are a variety of feature extraction methods such as WL, RMS, MAV, and VAR [19]. In this paper, we used WL to extract features in the time domain. The WL was the cumulative length of the waveform over time, which was calculated by an equation shown in Eq 1 [1]. N is the length of the EMG signal, and the EMG signal is X_n

$$WL = \sum_{n=1}^{N-1} |X_{n+1} - X_n| \tag{1}$$

The frequency domain of the EMG signal expresses information about neural anomalies and muscle fatigue, and is robust to noises [1, 5]. In this paper, we extracted the features in the frequency domain using the non-uniform filter bank. The inputted EMG signal was converted into the frequency domain using Fast Fourier Transform (FFT) and data was calculated using the designed non-uniform filter bank. The non-uniform filter bank used in the experiment is shown in Fig 13.

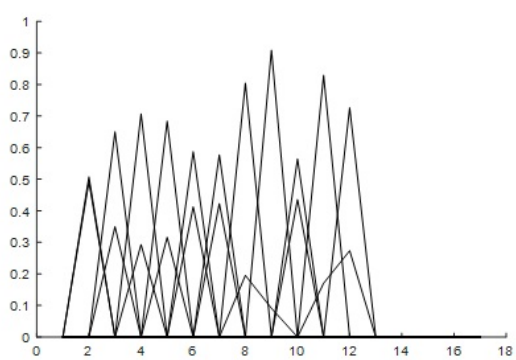


Figure 13: Non-uniform filter used for the experiment

PCA and LDA are well-known technologies for reducing data dimension. The PCA reduces the dimension by projecting data using the principal axis of all components, and the LDA finds the optimal projection in the feature space [12].

4 Experimental Results

Experimental results were obtained using the WL in time domain and the non-uniform filter bank in frequency domain. The data used in the experiment was UCI's sEMG basic hand movement upatras of the UCI and acquired EMG signals. The acquired EMG data were measured at two channels of the extensor carpi radial and the flexor carpi ulnaris of four person as shown in Fig 14, and the motions performed repeatedly were making a fist, rotating the wrist and raising the hand, performed as shown in Fig 15.

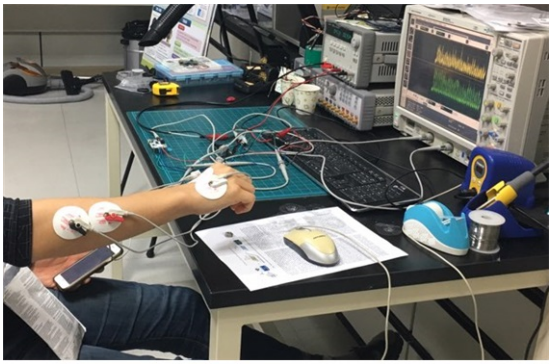


Figure 14: Acquiring EMG data

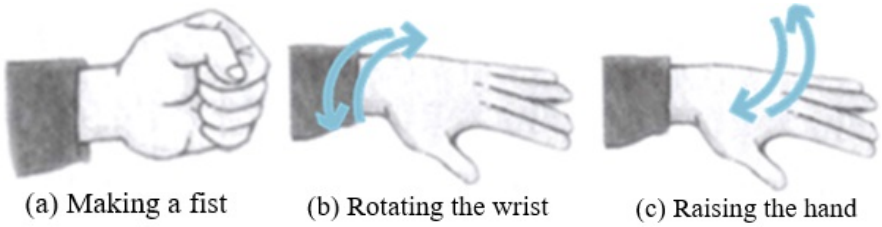


Figure 15: Three motions in the acquired EMG data

As shown in Fig 16, the acquired data shows the same recognition rate of 95% when SVM was used with the filter bank or filter bank and WL. As shown in Fig 17, the UCI data showed the recognition rate of 84.66% when ED was used with WL and the filter bank. The data acquired as a result of the personal identification experiments shows the highest personal identification rate of 95% on average for the motion of making a fist, and the rate of 85% when ED and KN were used WL and the filter bank as shown in Fig 18. The average personal identification rate using Hook or Snap operation of UCI data was the highest at 93.89% and the identification rate using ED with WL and the filter bank was 88.66% as shown in Fig 19.

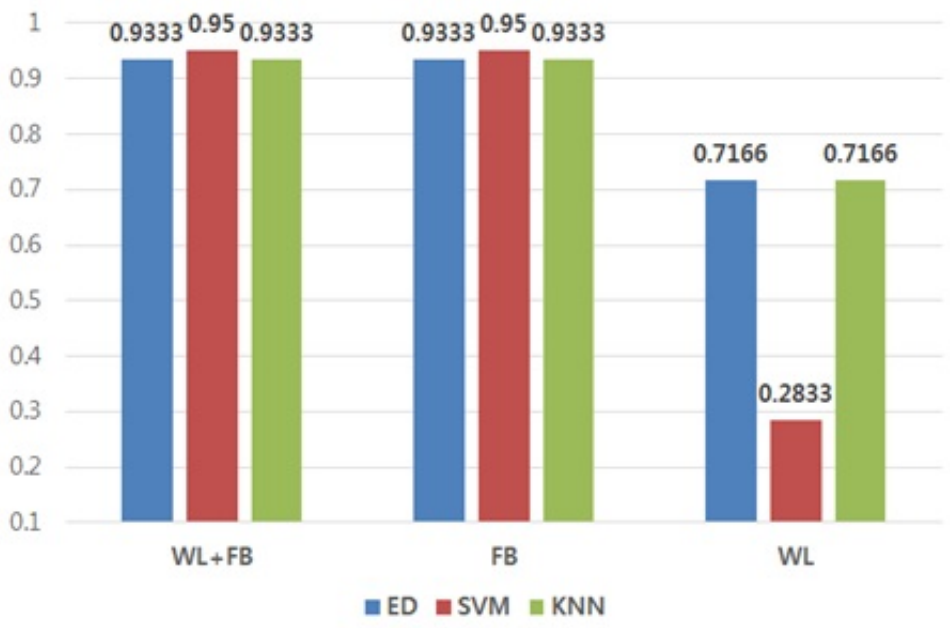


Figure 16: Result of EMG-based motion recognition experiment

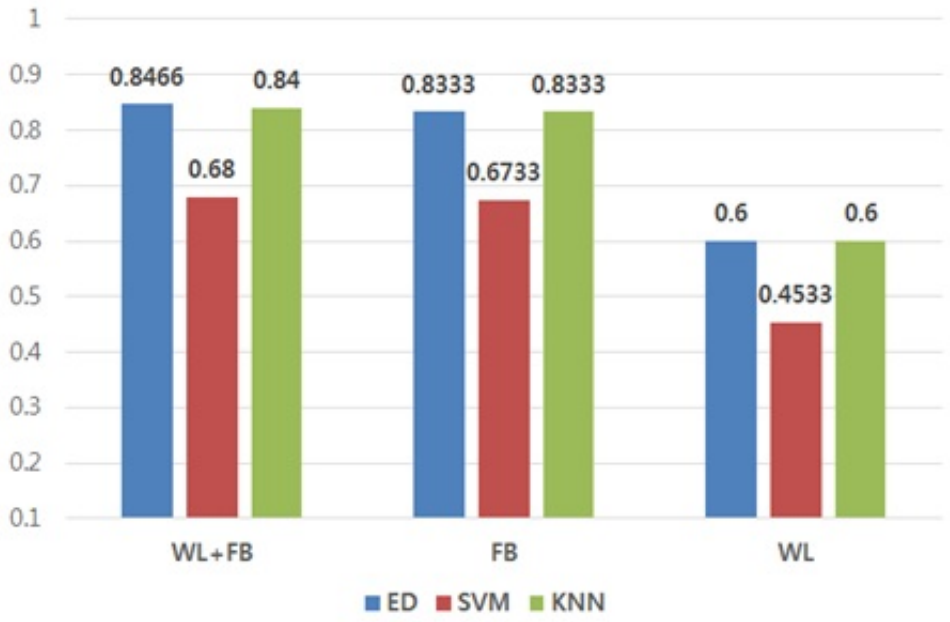


Figure 17: Result of UCI data-based motion recognition experiment

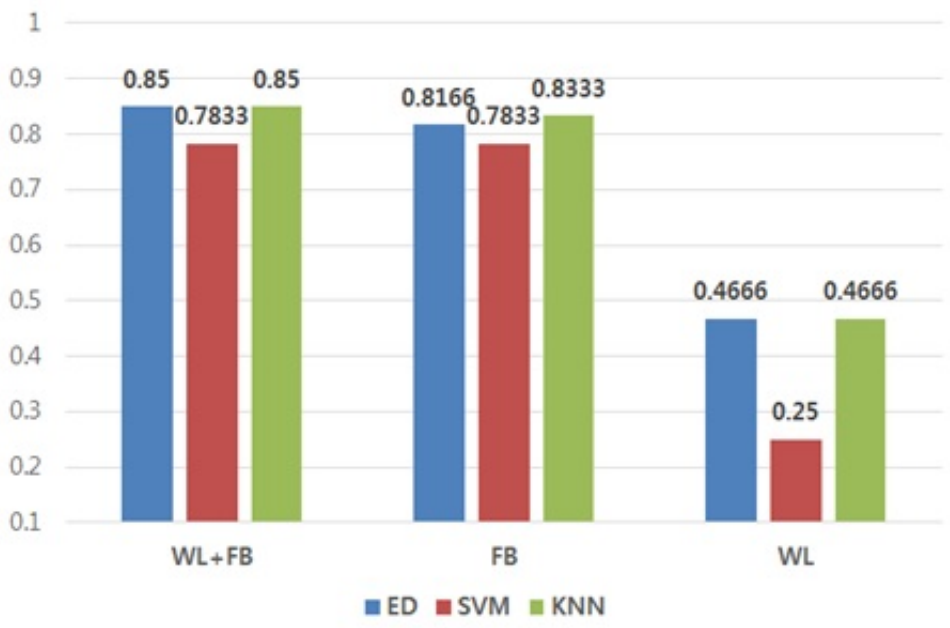


Figure 18: Result of EMG-based personal identification experiment

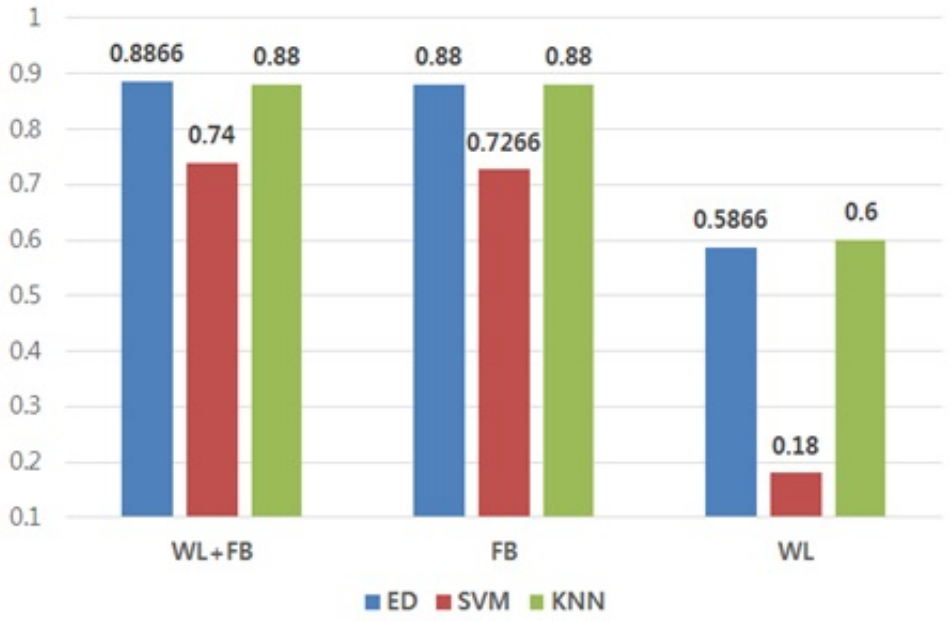


Figure 19: Result of UCI data-based personal identification experiment

5 Conclusion

The existing identify verification methods including identification using physical features are being exploited for various crimes due to many disadvantages. To solve this problem, studies using various behavioral characteristics have been actively conducted. Among them, EMG signals can be used in various ways, through required preprocessing depending on the purpose of use. Filters used for mo-

tion recognition and personal identification used are usually band-pass filters, low-pass filters, and notch filters, while feature extraction methods include scaling functions, filter banks, and PCA method.

As a result of motion recognition and personal identification experiments, the acquired EMG data showed the motion recognition performance of 95% and the UCI data showed 84.66%. As for the personal identification, the former showed the performance of 85% while the latter showed that of 88.66%. In the future, it is expected that the above technologies will be applied to motion-recognition based games to realize a virtual reality game that gives the same feeling as reality. It is also expected that they can be applied to a technique that allows only the persons, who are authorized based on their EMG signals, to control specific devices.

Acknowledgments

This work was partly supported by Institute for Information & communications Technology Promotion(IITP) grant funded by the Korea government(MSIP) (No.2017-0-00732,Next-generagion framework design for healthcare and self-coaching of elderly people based on smart devices) and the Human Resource Training Program for Regional Innovation and Creativity through the Ministry of Education and National Research Foundation of Korea (2015H1C1A1035823)

References

[1] B. S. Atal. Automatic recognition of speakers from their voices. *Proceedings of the IEEE*, 64(4):460–475, April 1976.

[2] Y.-J. Cho and J.-Y. Kim. The effect of the signal stationarity on the emg frequency analysis. *Journal of the Ergonomics Society of Korea*, 29(2):183–188, April 2010.

[3] H. K. Choi. MS to apply for patented technology to enjoy games with muscle movements, January 2010. `http://game.donga.com/49358/` [Online; Accessed on May 1, 2017].

[4] Y. J. Choi and H.-J. Yu. Human motion tracking based on semg signal processing. *Journal of Control, Auto mation, and Systems Engineering*, 13(8):769–776, August 2007.

[5] K. Englehart, B. Hudgin, and P. A. Parker. A wavelet-based continuous classification scheme for multifunction myoelectric control. *IEEE Transactions on Biomedical Engineering*, 48(3):302–311, March 2001.

[6] ForKnife. OBME(Rehabilitation therapy game using Own EMG signals, June 2015. `https://play.google.com/store/apps/details?id=appinventor.ai_quswodnjs719.game3&hl=ko` [Online; Accessed on May 1, 2017].

[7] H. Han, C. Choi, Y. Lee, S. Ha, and J. Kim. Development of an emg-based wireless and wearable computer interface. *Korea HCI Conference*, pages 240–244, February 2008.

[8] M. Haris, P. Chakraborty, and B. V. Rao. Emg signal based finger movement recognition for prosthetic hand control. In *Proc. of the Communication, Control and Intelligent Systems (CCIS'15), Mathura, India*, pages 194–198. IEEE, March 2015.

[9] L. J. Heon and L. J. Jae. Game for rehabilitation using electromyogram signal. *Korean Institute of Communication Sciences*, pages 164–165, June 2014.

[10] D.-H. Hwang, G.-Y. Sa, and Y.-T. Kim. Hand gesture recognition using semg signals of the forearm. *Journal of Korean Institute of Intelligent Systems*, 26(1):49–50, April 2016.

[11] C. Ishii and R. Konishi. A control of electric wheelchair using an emg based on degree of muscular activity. In *Proc. of the 2016 Euromicro Conference on Digital System Design (DSD'16), Limassol, Cyprus*, pages 567–574. IEEE, September 2016.

[12] H.-K. Jang, S.-M. Oh, and D.-S. Kang. The embodiment of the real-time face recognitions system using pca-based lda mixture algorithm. *The Institue of Electronics Engineers of Korea*, 41(4):45–50, July 2004.

[13] R. N. Khushaba, A. Al-Timemy, S. Kodagoda, and K. Nazarpour. Combined influence of forearm orientation and muscular contraction on emg pattern recognition. *Expert Systems with Applications*, 61:154–161, May 2016.

[14] S.-H. Kim, J.-H. Ryu, B.-H. Lee, and D.-H. Kim. Human identification using emg signal based artificial neural network. *Journal of the Institute of Electronics and Information Engineers*, 53(4):142–148, April 2016.

[15] P. Krishnamohan, M. S. Holi, et al. Gmm modeling of person information from emg signals. In *Proc. of the 2011 IEEE Recent Advances in Intelligent Computational Systems (RAICS'11), Trivandrum, India*, pages 712–717. IEEE, September 2011.

[16] C. H. Lee, S. I. Kang, S. H. Bae, J. W. Kwon, and D. H. Lee. A study of a module of wrist direction recognition using emg signals. *Journal of Rehabilitation Welfare Engineering & Assistive Technology*, 7(1):51–58, June 2013.

[17] K. Y. Moon. Biometrics technology status and prospects. *TTA journal*, (98):38–47, March 2005.

[18] S. B. Pan, Y.-W. Chung, K.-I. Chung, and J. H. Kim. Biometrics technology trends. *The Institute of Electronics and Information Engineers*, 29(5):529–537, May 2002.

[19] A. Phinyomark, S. Hirunviriya, C. Limsakul, and P. Phukpattaranont. Evaluation of emg feature extraction for hand movement recognition based on euclidean distance and standard deviation. In *Proc. of the 2010 International Conference on Electrical Engineering/Electronics Computer Telecommunications and Information Technology (ECTI-CON'10), Chiang Mai, Thailand*, pages 856–860. IEEE, May 2010.

[20] C. Sapsanis. *Recognition of basic hand movements using electromyography*. PhD thesis, Patras University, February 2013.

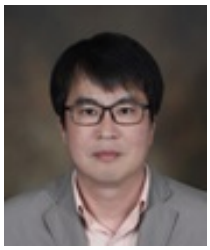
[21] C. Sapsanis, G. Georgoulas, A. Tzes, and D. Lymberopoulos. Improving EMG based classification of basic hand movements using EMD. In *Proc. of the 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC'13), Osaka, Japan*, pages 5754–5757. IEEE, July 2013.

[22] C. Savur and F. Sahin. Real-time american sign language recognition system using surface emg signal. In *Proc. of the 14th IEEE International Conference on Machine Learning and Applications (ICMLA'15), Miami, Florida, USA*, pages 497–502. IEEE, December 2015.

[23] J.-H. Yu, S.-H. Jeong, and D.-H. Kim. The gait phase recognition using two phase lda classifiers based on surface emg signals. *The Institute of Electronics Engineers of Korea*, pages 1009–1012, July 2013.

Author Biography

Jin Su Kim received B.S degree in the Department of Control, Instrumentation and Robot Engineering from Chosun University, Gwangju, Korea in 2016. He is currently a M.S. candidate in the Department of Control and Instrumentation Engineering at Chosun University. His current research interests include Image Processing, Embedded System, and Biometrics.



Sung Bum Pan received the B.S., M.S., and Ph.D. degrees in Electronics Engineering from Sogang University, Korea, in 1991, 1995, and 1999, respectively. He was a team leader at Biometric Technology Research Team of ETRI from 1999 to 2005. He is now professor at Chosun University. His current research interests are biometrics, security, and VLSI architectures for real-time image processing.