Finger Motion Detection for Human Activities Recognition using Single sEMG Channel

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Abstract: Today's aging population has recently become a significant problem, requiring a wearable health monitoring system for the elderly who are living alone. One of the focuses of this monitoring system is human activities recognition. We propose a wearable sensing method that is based on muscle's crosstalk information that uses only one sEMG channel (a pair of electrodes) to recognize five basic finger motions (thumb flexion, index flexion, middle flexion, ring & little flexion, and rest position) related to daily human activities. In the first step, an inter-electrode distance (IED) experiment was conducted to define the suitable IED for crosstalk information collection. In this experiment's recognition part, a conventional feature extraction method was adopted. The accuracy of each IED was compared and a suitable IED was defined (50 mm). In the second step, we propose two new features, the summit foot range (SFR) and summits number (SN), to represent the different patterns of finger motions' sEMG signals and adopted the minimal Redundancy Maximal Relevance (mRMR) feature selection method to improve the accuracy. An accuracy of over 87% was achieved using the improved recognition methodology compared to 81.5% when using the conventional one.

1 INTRODUCTION

The number of elderly is rapidly increasing, and there is an urgent need for a wearable health monitoring system that is both safe and comfortable for the elderly who are living alone. One of the focuses of this monitoring system is human activities recognition. Most of our daily life activities require us to use our fingers. The motions of the five fingers of a human hand play a leading role in detailed static activities such as typing, reading, writing, and using a mobile phone. Therefore, if the features of the motions of our fingers can be accurately extracted, it would be possible to recognize almost all human activities from only this five fingers' activity information. In particular, as the flexion motions are often the start of the finger motions while the extension motions are those that return back to the normal state, the five fingers' flexion motions need to be focused on first.

Two kinds of sensing approaches have mainly been proposed in the field of finger motion recognition, vision sensor based and non-vision sensor based.

There are several vision sensor based approaches. Lee et al., 2011, for example, have developed a finger motion recognition method that detects the finger's angle change using a video sensor. Finger motions like moving, clicking, or pointing can be recognized by analyzing the contour of the tracked finger. However, because of the immobility of the video sensor, it is difficult to use this approach for outdoor recognition and other kinds of moving activities recognition.

On the other hand, there are mainly two kinds of sensors for the non-vision sensor based approach. One is the gyroscope sensor. For example, Schaechter et al., 2006, have developed a device to detect finger motions based on a Micro Electro Mechanical Systems (MEMS) gyroscope sensor that is positioned on the fingers. However, using plenty of gyroscope chips and cables will decrease the flexibility of the fingers and greatly affect the user's hand activities.

The surface electromyography (sEMG) sensor is becoming an exciting tool for use in finger motion recognition because it can efficiently and accurately collect the signal from a finger's detailed motion.

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However, previous researches could only achieve an acceptable level of accuracy for finger motion recognition using multiple sEMG channels (Ishikawa et al., 2010; Tenore et al., 2009; Nagata et al., 2007). The excessive use of channels not only makes the subjects uncomfortable but also takes lots of time for the electrodes' placement. They used more than one sEMG channel (a pair of electrodes) because the accuracy when using only one sEMG channel was not acceptable. For example, Nagata et al., 2007, have developed a finger motion recognition system that is based on 96 pairs of electrodes, which can recognize 18 kinds of finger motions and achieve an average accuracy of 95%. However, when the number of electrodes was reduced to one pair, the accuracy dropped to 33%. Therefore, how to increase the portability without affecting the accuracy has become a significant research topic.

According to the above statement, we propose a new finger motion recognition methodology using one sEMG channel that is wearable and convenient.

This paper is organized as follows. The benefit of using a muscle's crosstalk information, which is the basis of our sensing method, is described in Section 2. The signal acquisition protocol is described in Section 3. The recognition methodology adopted in the inter-electrode distance (IED) experiment is illustrated in Section 4. In Section 5, the IED experiment is described and a suitable IED is defined based on the recognition results. In Section 6, the improved recognition methodology is introduced. The recognition results of the improved recognition methodology are discussed in Section 7. Finally, the conclusion and future works are presented in Section 8.

2 MUSCLE'S CROSSTALK

A pair of electrodes is usually placed close to each other, aiming to collect one specific muscle's sEMG signal without much crosstalk from the other muscles. If the IED (inter-electrode distance) becomes larger, other muscles' crosstalk information will be recorded. However, it was previously found that the crosstalk can produce unique sEMG signals' patterns that are useful for classification. In addition, a large IED can make the negative effect of electrodes' displacement smaller by detecting a signal that contains multiple muscles' activity information (Hudgins et al., 1993).

In our case, as we only use one sEMG channel to collect the finger motions' signals, we need to record the signals of multiple muscles together. So, we enlarged the IED, and thus, the crosstalk information of the muscles can be recorded.

3 SIGNAL ACQUISITION PROTOCOL

Eight intact-limbed subjects (3 females and 5 males, 21-46 years old) with no injury history or nerve problems on their right forearms participated in our research.

After their right forearms were wiped with first an alcohol tissue and then a dry tissue, a pair of Ag/AgCl adhesive electrodes was attached in the area around the flexor pollicis longus muscle, the flexor digitorum superficialis muscle, and the flexor digitorum profundus muscle, which mainly are associated with the fingers' flexion motions, as shown in Table 1 (Moore et al., 2010). The center of the two electrodes is on the midline of the forearm's palmer surface, and 0.75 of the distance from the wrist to the olecranon. This placement ensures that we can collect clear and stable signals from all three muscles, which can be easily segmented.

Table 1: Forearm muscles and their corresponding fingers' flexion motions.

Muscle	Finger motions
Flexor pollicis longus	Flexion of thumb
Flexor digitorum superficialis	Flexion of index, middle, ring, and little finger (proximal interphalangeal joints)
Flexor digitorum profundus	Flexion of index, middle, ring, and little finger (distal interphalangeal joints)

The sEMG signal is collected by sEMG active dipole (emgPLUX) sensor, which is connected to a wearable signal acquisition device (BioPLUX[1] research unit) sampling at 1 kHz with a resolution of 12 bits. This device can send the signal (in real-time) via Bluetooth to the computer. The sEMG signal is visually inspected on the computer to ensure that it is stable (MonitorPlux v2.0, PLUX - Engenharia de Biosensores, Lda.).

The five basic finger motions related to daily activities performed by the eight subjects are: thumb flexion, index flexion, middle flexion, ring & little flexion, and rest position. As we seldom flex our ring or little finger separately in daily life, the combination of the ring and little fingers' flexion was performed.

The subjects were asked to perform their finger motions at a relatively fast speed like they usually would in daily life activities. In order to cut only the flexion motion's signal out in the signal segmentation step, the final position of each flexion motion was held for a period of approximately 1 s, resulting in some muscles' contraction signals. As to avoid the effect of muscle fatigue, each motion was repeated 10 times, and the subjects had to relax for approximately 1 min before the next motion started. A total of 400 finger-motion data were collected.

4 CONVENTIONAL RECOGNITION METHODOLOGY

In this section, we illustrate a conventional recognition methodology adopted in the IED experiment, as shown in Figure 1.

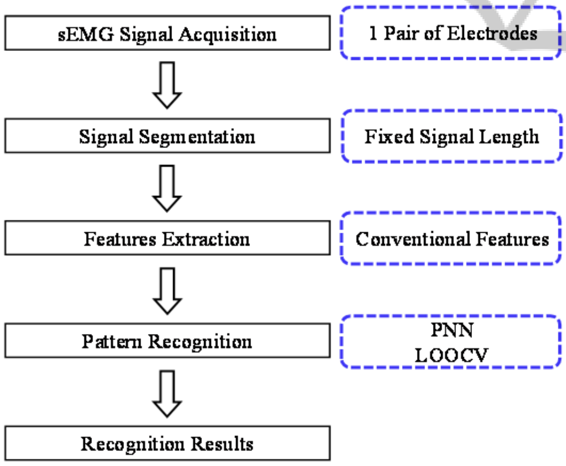

Figure 1: Conventional recognition methodology of IED experiment.

4.1 Signal Segmentation Method

In order to cut only the flexion motion's signal out, we manually segmented each motion. As shown in Figure 2, we set the signal length at 400 ms, which ensured that we cut the flexion motion's entire signal out. It is worth noting that the signal segmented also contained some muscles' contraction signals as the subjects performed their flexion motions at different speeds. However, since the flexion motion's signal is much larger than the contraction's signal, the extracted features mainly belong to the flexion motion.

4.2 Conventional Feature Extraction Method

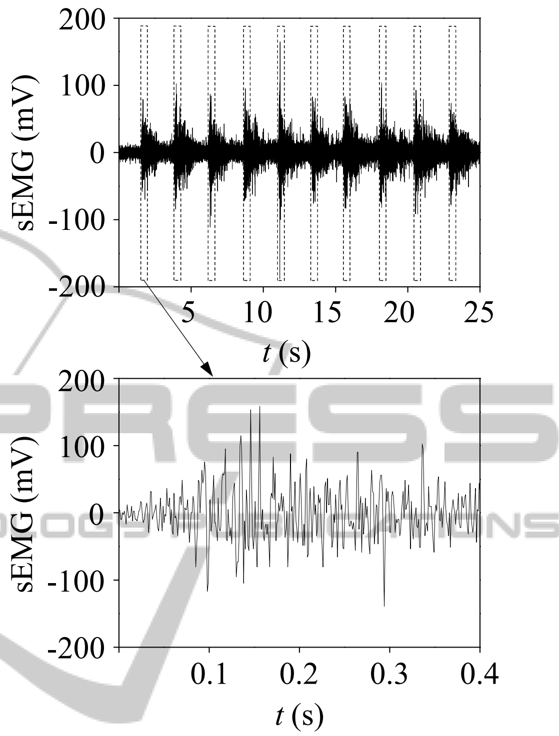

Figure 2: Example of sEMG signals' segmentation process. Each window size in the figure at the top is 400 ms. The signal segmented in the bottom figure shows that it also contains the muscles' contraction signal.

It has previously been demonstrated that Time Domain (TD)-Autoregressive (AR) features are useful and efficient when extracting the features of finger motions' sEMG signals (Al-Timemy et al., 2013; Hargrove et al., 2007; Hudgins et al., 1993). Hargrove et al., 2007, showed that the TD-AR features could achieve higher performance than that of other feature extraction methods such as Fourier transform and wavelet transform for the detection of hand motions with sEMG signals.

The TD-AR features we adopted were the AR model coefficients (order 6), root mean square (RMS), mean absolute value (MAV), waveform length (WL), zero crossings (ZC), and slope sign changes (SSC). It is worth noting that the dead-zone of the zero crossings and the slope sign changes was set to 12 mV because the noise became a little larger after we enlarged the IED.

We adopted the overlapping window method to extract each feature. The window size was 200 ms and the interval of the adjacent window was 40 ms. The average value of each feature for all the windows was calculated, resulting in 11 features for each sample. Each time domain feature was linearly normalized to [0,1] before inputting the classifier.

4.3 Classification and Validation Method

The probabilistic neural network (PNN) was selected as the classifier (Specht et al., 1990). PNN is a kind of artificial neural network, which has an excellent performance reputation for complex biological signals like sEMG signals.

As for the validation, we adopted the leave-one-out-cross-validation (LOOCV) since we have a relatively small database (400 samples)(Cawley, 2006). In our case, LOOCV involves using a single observation from the original samples as the validation data, and the remaining observations as the training data. The validation was repeated 400 times and the average accuracy was calculated.

5 INTER-ELECTRODE DISTANCE EXPERIMENT

In this section, we compare the recognition accuracy of different IEDs using the conventional recognition methodology to define a suitable IED.

5.1 Inter-electrode Distance Selection

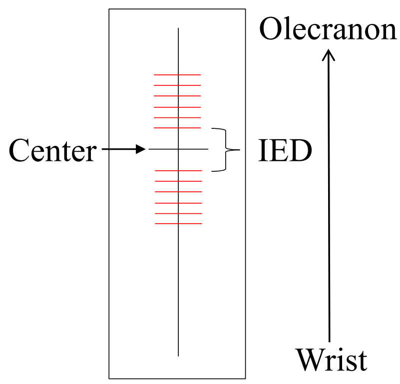

Figure 3: Placement of pair of electrodes on forearm for IED experiment. The center of the two electrodes is on the midline of the forearm's palmer surface, and at 0.75 of the distance from the wrist to the olecranon. The IED increases from 30 to 80 mm at an interval of 10 mm.

We selected IEDs of 30, 40, 50, 60, 70, and 80 mm as shown in Figure 3. These IEDs correspond to the amount of crosstalk information collected ranging from only a few to large amount. In addition, 30 mm means that the two electrodes were placed very near to each other, which is the conventional placement method.

We separately collected each finger motion's sEMG signals from six different IEDs.

5.2 Recognition Results

The accuracy of the six different IEDs using the conventional recognition methodology are shown in Figure 4.

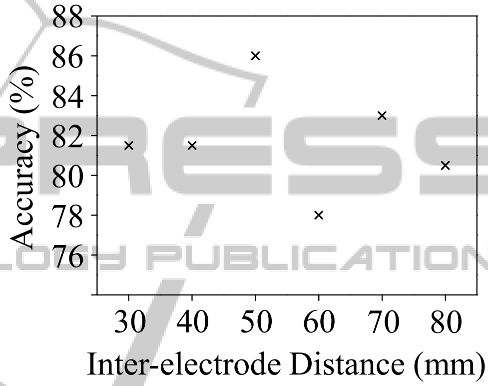

Figure 4: Recognition results from six different IEDs.

5.3 Discussion and Conclusion

As shown in Figure 4, the accuracy at 30 mm was 81.5%, which is not very satisfying. However, when we enlarged the IED to 50 mm, the accuracy increased to the highest level of 86%. So, we defined 50 mm as the suitable IED for collecting a wide range of crosstalk information without too much noise, while still maintaining the unique pattern of each motion's signal. If the IED is smaller than 50 mm, the crosstalk information of multiple muscles cannot be fully recorded. And if the IED is larger than 50 mm, the recorded crosstalk information is too universal for creating unique signal patterns. In addition to the crosstalk information, the enlarged IED is insensitive to the variations in anatomy of the subjects, which often causes individual differences.

6 IMPROVED RECOGNITION METHODOLOGY

As the effectiveness of the features and the overtraining of the classifier may significantly affect the accuracy, apart from defining the suitable IED (50 mm), we also started to think about proposing some new features and adopting a feature selection method to improve the level of accuracy.

Our improved recognition methodology with the 50-mm IED mainly contains two new features for the features extraction and a feature selection method adopted to decide the optimal feature set.

In this section, we introduce the methodology that is shown in Figure 5.

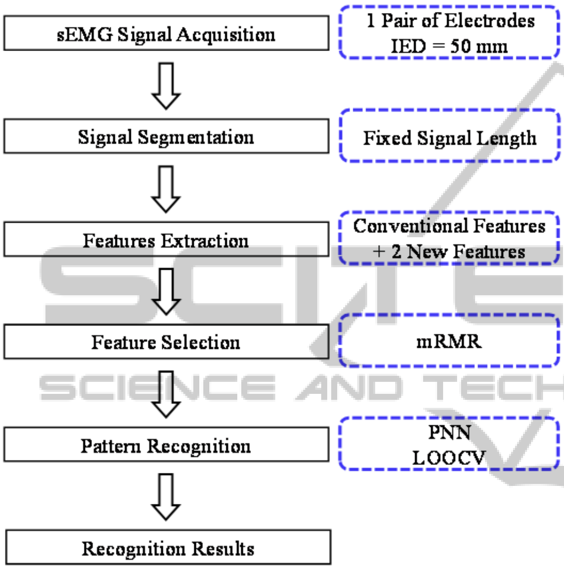

Figure 5: Improved recognition methodology.

6.1 Newly Proposed Features

In this sub-section, we propose two new features to represent the different patterns of finger motions' sEMG signals.

6.1.1 Summit Foot Range (SFR)

We inspected the different motions' sEMG signals, and found that the foot ranges of the summits are different for different motions, as shown in Figures 6 and 7. The foot ranges can be interpreted as the frequency information of the summits. Therefore, a feature called the summit foot range is proposed to represent the frequency information of these summits.

The SFR in an overlapping window is defined as the following formula:

$$SFR = \Sigma \ (\text{Foot2} - \text{Foot1}) / N, \qquad (1)$$

where Foot2 and Foot1 are the two feet of each summit, and N represents the number of summits found in an overlapping window.

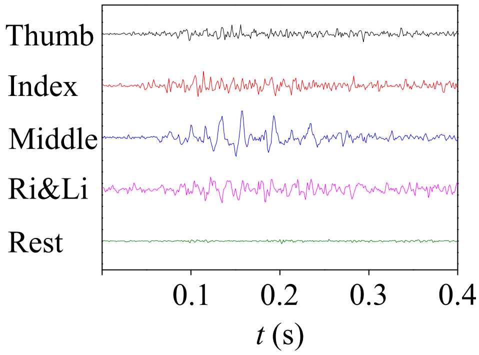

Figure 6: Example of different patterns of finger flexion motions' sEMG signals. Ri&Li represents the ring & little flexion motion.

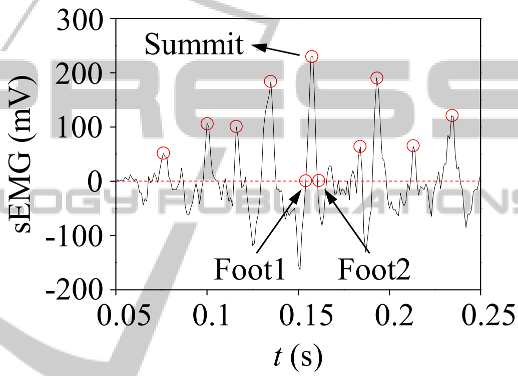

Figure 7: Example of summits and two feet of one summit (Foot1 and Foot2), which is 50– 250 ms of middle flexion motion's signal in Figure 6.

A MATLAB function called *findpeaks*[2] is adopted to find the summits.

We defined several parameters in this function so that the patterns of different motions' sEMG signals can be clearly extracted.

- *MINPEAKHEIGHT*: In order to avoid extracting noise's features, the minimum height of a summit should be set. The rest position's signal can indicate that the amplitude of noise is 12 mV. So, the *MINPEAKHEIGHT* was set to 12 mV.
- *MINPEAKDISTANCE*: The minimum distance between summits was set to 3 ms to avoid misdetecting small peaks that occur in the neighborhood of a summit.

We adopted the zero crossing method to find the feet that are near 0 mV when the foot's amplitude is not exactly 0 mV (Hudgins et al., 1993).

6.1.2 Summits Number (SN)

The average number of summits found in all the overlapping windows was also introduced as a feature to strengthen the SFR by complementing the

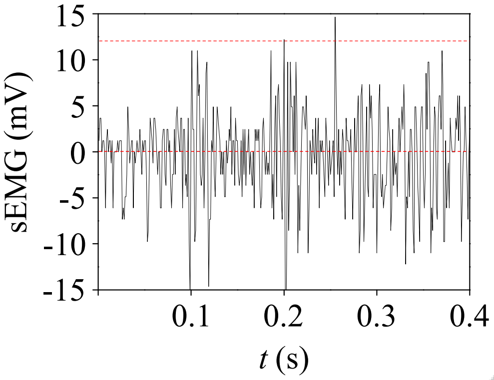

Figure 8: Example of the rest position's signal, which indicates the amplitude of noise. The red and dashed lines show the *MINPEAKHEIGHT* of 12 mV.

frequency information of the summits. This feature is called the summits number.

6.2 Feature Set Optimization by mRMR

The minimal Redundancy Maximal Relevance (mRMR) feature selection method can increase the recognition accuracy by ranking the importance of the features in regards to both their relevance and information content (Peng et al., 2005).

We ranked all 13 features by adopting the mRMR, and compared the accuracy by increasing the number of input features from a ranking of 1 to 13, as listed in Table 2.

Table 2: Features' ranking using mRMR.

Ranking	Feature	Cumulative accuracy
1	SN	57.8%
2	AR1	71%
3	RMS	75.8%
4	SFR	76%
5	WL	78.3%
6	AR2	84%
7	ZC	84.8%
8	MAV	84.8%
9	AR6	84.8%
10	SSC	87%
11	AR3	86.8%
12	AR5	87.3%
13	AR4	86.8%

7 DISCUSSION

As listed in Table 2, the accuracy was the highest when eliminating AR4, which is ranked as the lowest feature when using the mRMR. So, the optimal feature set is: SN, AR1, RMS, SFR, WL, AR2, ZC, MAV, AR6, SSC, AR3, and AR5. The highest accuracy we have found thus far is 87.3%, compared to 81.5% for the conventional methodology with the conventional placement method of IED of 30 mm.

In addition, when we used our improved methodology to recognize the motions' signals collected when the IED is 30 mm, the accuracy decreased a little, as listed in Table 3. This may be because our newly proposed features are not very suitable for sEMG signals collected when the IED is 30 mm.

Table 3: Comparison of recognition results of conventional and improved methodology with IED of 30 and 50 mm.

IED (mm)	Conventional methodology	Improved methodology
30	81.5%	81.3%
50	86%	87.3%

The detailed improvement of each finger motions' accuracy is proven by the confusion matrixes noted in Tables 4 and 5. We determined from the confusion matrixes that our improved recognition methodology contributed to a universal increase in almost all the motions' accuracy. In particular, an increase of 17.5% was achieved for the flexion of the middle finger. This shows that our improved recognition methodology can generally improve the accuracy of almost all the motions, indicating that other motions besides the five basic motions can be accurately recognized as well.

Table 4: Finger motion recognition confusion matrix of conventional recognition methodology (IED = 30 mm).

Motion	Accuracy (%)				
	Thumb	Index	Middle	Ri&Li	Rest
Thumb	**71.3**	10	1.2	17.5	0
Index	8.8	**90**	0	1.2	0
Middle	3.7	0	**75**	21.3	0
Ri&Li	7.5	3.7	17.5	**71.3**	0
Rest	0	0	0	0	**100**

The confusion matrix in Table 5 helped us determine that the recognition error mainly comes from the adjacent fingers. There are basically two explanations for this phenomenon. One is that the subjects often could not flex a single finger without moving the adjacent fingers, causing other finger motions' sEMG signals to be collected. The other explanation is that the crosstalk information of the adjacent muscles may still be a little universal for creating the different patterns of the finger motions' sEMG signals.

Table 5: Finger motion recognition confusion matrix of improved recognition methodology (IED = 50 mm).

Motion	Accuracy (%)				
	Thumb	Index	Middle	Ri&Li	Rest
Thumb	**81.3**	13.8	1.2	3.7	0
Index	5	**91.3**	0	2.5	1.2
Middle	0	0	**92.5**	7.5	0
Ri&Li	6.2	2.5	20	**71.3**	0
Rest	0	0	0	0	**100**

The two new features (SFR and SN) and the mRMR together contributed to a 1.3% increase in accuracy (87.3% compared to 86%), which is a relatively small improvement. However, as noted in Table 2, the mRMR ranks the SN and SFR in 1st and 4th place, respectively, showing they are very effective features of the sEMG signals for finger motion recognition. Since we did not normalize the amplitude of the signals, SFR and SN can have a robust performance regarding the individual differences because they are not related to the amplitude information.

However, although the recognition results by adopting the mRMR show that only AR4 should be eliminated, it also indicates that if we do not need to have the highest level of accuracy, a more compact feature set can be selected (SN, AR1, RMS, SFR, WL, and AR2), resulting in an accuracy of 84%. This result shows us that by adopting the mRMR, we can determine a relatively suitable feature set that can significantly reduce the computing time with only a slight decrease in accuracy.

8 CONCLUSIONS

We proposed a wearable sensing method based on the muscle's crosstalk information that uses only one sEMG channel to recognize five basic finger motions (thumb flexion, index flexion, middle flexion, ring & little flexion, and rest position) related to daily human activities. A suitable inter-electrode distance was defined (50 mm) from the inter-electrode distance experiment to improve the accuracy. In addition, two new features were proposed and a feature selection method was adopted, resulting in an accuracy of 87.3% compared to 81.5% when using the conventional methodology with an IED of 30 mm. Our results show that the improved recognition methodology is not only effective for detecting finger motions, but also is insensitive to individual differences.

The recognition methodology still needs improvement. The effectiveness of our methodology in recognizing other motions besides the five basic motions should also be reexamined. As for its application, we need to adopt the wearable sensing method and the improved recognition methodology for recognizing daily human activities like typing, reading, writing, and using a mobile phone.

REFERENCES

Al-Timemy, A., Bugmann, G., Escudero, J., and Outram, N., 2013. Classification of finger movements for the dexterous hand prosthesis control with surface electromyography. *IEEE Journal of Biomedical and Health Informatics, Vol. 17, No. 3*, pages 608-618.

Cawley, G. C., 2006. Leave-one-out cross-validation based model selection criteria for weighted LS-SVMs. In *Proceedings of the International Joint Conference on Neural Networks (IJCNN'06)*, pages 1661-1668.

Hargrove, L. J., Englehart, K., and Hudgins, B., 2007. A comparison of surface and intramuscular myoelectric signal classification. *IEEE Transactions on Biomedical Engineering, Vol. 54, No. 5*, pages 847-853.

Hudgins, B., Parker, P., and Scott, R. N., 1993. A new strategy for multifunction myoelectric control. *IEEE Transactions on Biomedical Engineering, Vol. 40, No. 1*, pages 82-94.

Ishikawa, K., Toda, M., Sakurazawa, S., Akita, J., Kondo, K., and Nakamura, Y., 2010. Finger motion classification using surface-electromyogram signals. In *Proceedings of IEEE/ACIS 9th International Conference on Computer and Information Science (ICIS)*, pages 37-42.

Lee, D., and Lee, S., 2011. Vision-based finger action recognition by angle detection and contour analysis. *ETRI Journal, Vol. 33, No. 3*, pages 415-422.

Moore, K. L., Arthur F. D., and Anne M. R. A., 2010. *Clinically oriented anatomy*. Wolters Kluwer Health, 6th edition, pages 748-750.

Nagata, K., Ando, K., Magatani, K., and Yamada, M., 2007. Development of the hand motion recognition system based on surface EMG using suitable measurement channels for pattern recognition. In *Proceedings of Engineering in Medicine and Biology Society, 29th Annual International Conference of the IEEE*. IEEE, pages 5214-5217.

Peng, H., Long, F., and Ding, C., 2005. Feature selection based on mutual information criteria of max-dependency, max-relevance, and min-redundancy. *IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 27, No. 8*, pages 1226-1238.

Schaechter, J. D., Stokes, C., Connell, B. D., Perdue, K., and Bonmassar, G., 2006. Finger motion sensors for fMRI motor studies. *Neuroimage, Vol. 31 No. 4*, pages 1549-1559.

Specht, D. F., 1990. Probabilistic neural networks. *Neural Networks, Vol. 3, No. 1*, pages 109-118.

Tenore, F. V. G., Ramos, A., Fahmy, A., Acharya, S., Etienne-Cummings, and R., Thakor, N. V., 2009. Decoding of individuated finger movements using surface electromyography. *IEEE Transactions on Biomedical Engineering, Vol. 56, No. 5*, pages 1427-1434.

Notes.

[1]http://www.bioplux.com/home.

[2]http://www.mathworks.co.jp/jp/help/signal/ref/findpeaks.html?lang=en.