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Research on EMG-based Classification of Hand Movements using Four Electrodes Arrangements on Forearm

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Abstract: Although various types of myoelectric prosthetic hands using surface electromyogram have been developed, the placement of electrodes to acquire myoelectric potential needs to be adjusted by a specialist, and myoelectric potential differs from individual to individuals, so it needs to be adjusted to the individual user. Also, it is not covered by health insurance in Japan, and there are technical fees for the product price and initial setup. We propose a method of electrode placement and pretreatment that does not require much expertise by placing electrodes at the mid-forearm in the form of a wristband to improve them. In this study, we report the effects of muscle potential measurements on the pattern discriminator and the estimation of the useful measurement points by fixing four electrodes arranged in the form of wristbands. In this proposed method, the accuracy of identification is more than 95 %.

Keywords: Surface electromyogram, myoelectric potential, myoelectric prosthetic hand, pattern discrimination

1. Introduction

Nowadays, myoelectric prosthetic hands are used as a means of enriching daily lives of people who lost their hands and arms part congenitally (or acquired handicapped persons). According to a survey related to the problems in daily lives in 2016 by MHLW (Ministry of Health, Labour and Welfare in Japan), the number of the physically handicapped persons whose upper limbs have the problems is 620,000 in Japan and many people want to use myoelectric prosthetic hands. The myoelectric potential has to be measured before using the myoelectric prosthetic hands. In this case, the acquired handicapped persons who lost their upper arms have the feelings of moving the amputated arms or hands in the place of missing limbs. This is called "phantom limb". Using the myogenic potential signals which are generated when the persons try to move their phantom limbs, the myoelectric prosthetic hands control the movements. In addition, cosmetic upper limb prostheses are used the most as upper limb ones. Because of this, it is inconvenient in some daily lives. Therefore, the development of the upper limb prostheses that can be controlled by reflecting the user's intention is expected and their development have been carried out in recent years [1], [2].

According to the previous studies, the electrode for electromyography measurement is arranged at the point of large movement of research subjects' arm muscles and they use a lot of electrodes [3], [4]. Thus, the useful surface myoelectricity potential can be easily taken. In the previous studies, the methods of pretreatment of frequency analysis, integration for electromyography measurement, and independent component analysis; in addition, classifiers are SVM (Support Vector Machine) and Neural Network [5-8]. As described the above, using surface electromyography, the adequate assignment of the electrode is required to take surface myoelectricity measurement. Therefore, the adjustment of the electrode for electromyography measurement by an expert is needed. Even though the expert does not do such adjustment, it can be easily done by using our proposed method. In this study, we propose the method to assignment of

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the electrode for electromyography measurement simply. The proposed method leads to improvement of user convenience.

The proposed method is a combination of the way that four electrodes are assigned (attached) at the middle of arm like a wrist band and the way that pretreatment method uses the ratio of the myoelectric potentials as shown in Fig. 1. Thus, the proposed method has advantage that any person having no expert knowledge can assign the electrodes. In this method, the assignment of electrodes was decided based on the previous studies. The acquired surface electromyograms are smoothed, so as to be applicable to a pattern recognition; after that, the influence of the ways of feature quantity extraction evaluates. Using the surface myoelectricity potential (value) obtained by the assignment of the electrodes (like a wrist band), we create a classifier and evaluate the classifier's accuracy. Therefore, we can evaluate the effectiveness and availability of the proposed method.

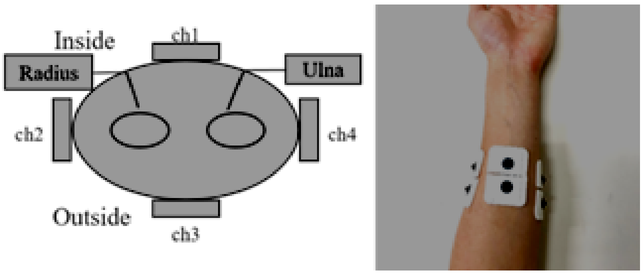

Fig. 1 - Proposal measurement position

2. Experiment Method

2.1 Myoelectric Signal

Electromyogram (EMG) shows the recording and display of occurring myoelectric potential when muscle fibers are receiving a motion command muscle fiber. Therefore, EMG involves the motion command information, hence it is useful to estimate amputees' intention of motion. To control myoelectric prosthetic hands, it needs processing for high accuracy pattern analysis, and high recognition ability when acquiring the myoelectric potential. The methods of measuring the myoelectric potential are divided into two broad types by the electrode used for it. One method is using surface electrodes attached to the skin's surface that is called "surface electromyogram method". The record of the results using this method is called "surface electromyogram". Another method is using needle electrodes that is called "needle electromyogram method". The record using this method is called "needle electromyogram". In this study, we use "surface electromyogram method", which is often used for kinetic analysis in a noninvasive way. We acquire "surface electromyogram" and it is used for the experiment.

2.2 Measuring Method

In the motion identification system of this study, the myoelectric potential acquired from the arm is amplified by using the head amplifier and biological amplifier; after that, the surface myoelectricity potential is acquired by using A/D conversion as shown in Fig. 2.

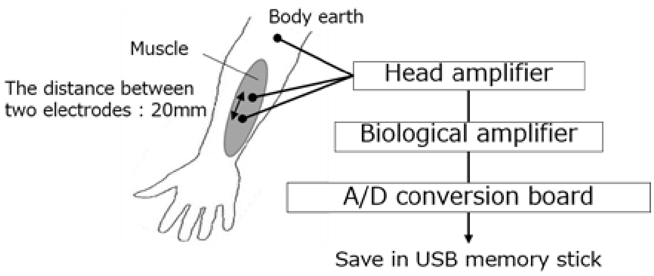

Fig. 2 - Measurement system

The six kinds of motion carried out in this study are Relaxation, Grasping, Opening, Palmar flexion, Dorsal flexion, and Ulnar flexion as shown in Fig. 3. The electrode arrangement using the conventional method is the nearest measurement position of each active muscle as shown in Fig. 4 and the proposed arrangement method is that the electrodes are assigned at the middle of the arm like a wrist band as shown in Fig. 1. The disposable electrodes are placed and the surface myoelectricity potentials are measured when the six kinds of specified motion are carried out using the method of bipolar detection. The method of bipolar detection is a way that two electrodes are placed at the measurement point and the body earths are placed at the bone end parts which are not affected by occurring voltage from the measurement point. It is how the potential difference between each measurement point electrode and the body earth is measured. Because of this, the occurrence of noise is mitigated, and the more accurate myoelectric potential can be measured. The contents of this experiment are explained before that and the experimenters agreed with it. The six motions of measurements for the myoelectric potential are Relaxation, Grasping, Opening, Palmar flexion, Dorsal flexion, and Ulnar flexion were carried out in turn. We explained in the experiments that it would come back to the motion of "Relaxation" after each motion. This series of streams is considered as one set and the total measurements of the myoelectric potential are 50 sets in this experiment. The numbers of data in the proposed method and conventional one is 300 (the total per person is 600).

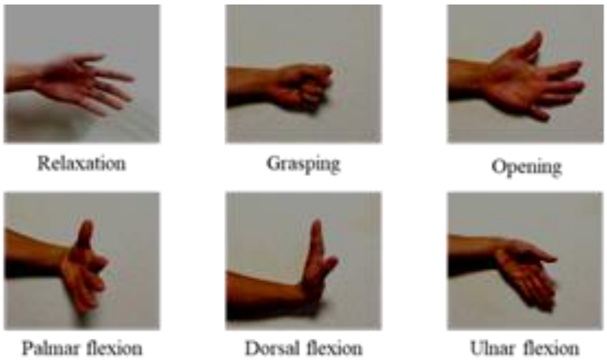

Fig. 3 - Movements

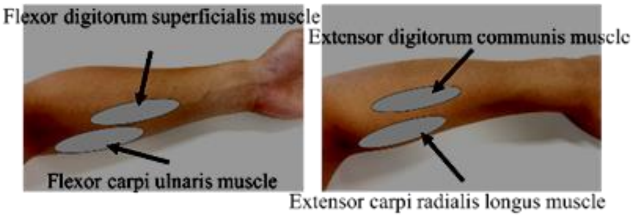

Fig. 4 - Conventional measurement position

The experimenters are the five healthy men, and their age is 22 years old. In addition, the conditions of the experiment are (shown in Table 1) "amplifier gain: 74 dB", "A/D conversion: 16 bit", "sampling frequency: 6,000 Hz", "measurement time: 500 msec", "high-pass filter (cutoff frequency) : 5 Hz", "low-pass filter (cutoff frequency) : 1000 Hz", "notch filter (frequency band) : 59.5-60.5 Hz", and "electric skin resistance : 5 kΩ or less".

Table 1 - Measurement conditions

Head amplifier	BA-U001
Biological amplifier	BA-1008 74[dB]
A/D conversion board	ADA16-32/2(CB)F 16[bit], 500[kS/s]
Sampling rate	6,000[Hz]
Sampling time	500[ms]
High-pass filter	5[Hz]
Low-pass filter	1,000[Hz]
Notch filter	59.5 – 60.5[Hz]
Skin resistance	Less than 5[kΩ]
Participants	Five 22-years-old males

2.3 Feature Quantity Extraction

If the measured myoelectric potential is kept as it is, it is hard to handle for that, we extract the feature quantity as preprocessing. Using the feature quantity, we evaluate motion identification. The feature quantity is often used as a frequency information; however, we use "Root Mean Square (RMS)" and "Integrated EMG (IEMG)" of fully added the

RMS as the feature quantity as shown in the third row of Fig. 5. The first and second row in Fig. 5 show the measurement and their absolute values, respectively.

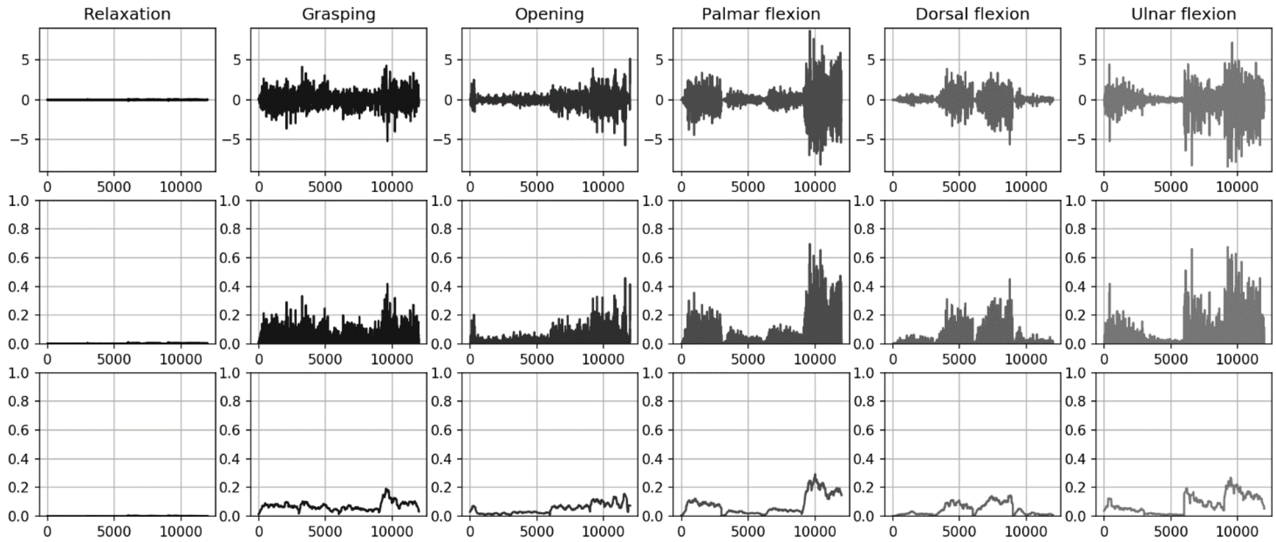

Fig. 5 - Scheme of preprocessing

Root Mean Square (RMS)

The myoelectric potential signals are squared and averaged in a certain span of time and take the root value (effective value) (RMS). In Eq. (1), *e*(*t*), *i*, and *k* mean the myoelectric potential signals, the electrode position, and motion of the hand, respectively. The change in the effective values with time is acquired by sequentially shifting the time range to be measured by degrees (time variation of the effective value). In this study, the time to be calculated is 41 msec and the effective values is acquired per 250 samples. The reason for this is that the time from the generation of the myoelectric potential signals to the generation of the muscle strength is approximately 100 msec and the requirement of avoiding the feeling of the time lag for the operator by the above calculation method can be done. Considering the classification processing, the calculation time of 41 msec is adequate.

$$RMS_i^k(t) = \sqrt{\frac{1}{T}\int_t^{t+\tau} e_i^{k^2}(t+\tau)d\tau} \quad (1)$$

Integrated IEMG (IEMG)

IEMG means the integrated value of the rectified waves in a certain span of time. In other words, it means a total discharge amount of that. The calculation of IEMG is that the input data is multiplied by the forgetting rate coefficient. In this study, this method did not apply the calculation instead of RMS method because the integration values of RMS are IEMG. The reason is that drawing the waveform in the case that it involves the forgetting rate is similar to RMS processing one as shown in Eq. (2).

$$IEMG_i^k = \sum_{t=1}^{3000} RMS_i^k(t) \quad (2)$$

2.4 Feedforward Neural Networks

Feedforward Neural Networks (FFNNs) arranges the units in a layered manner and the architecture is that the units are connected with only adjacent layers, and information is propagated in the forward direction from input to output as shown in Fig. 6. Some input data are multiplied by the different weights and added in each unit, and the result is calculated to become one output and propagated to the next layer. As a matter of fact, the output value is multiplied by a value of activation function. In this study, the sigmoid function is used as the activation one as shown in Eq. (3) and the output of each unit is shown in Eq. (4) and Eq. (5). The learning algorithm is used for the backward propagation method. The method adjusts the network weights and minimizes the error function. The error function is calculated by difference d_{nk} between the teacher signals and the results of output. The error function is used for the cross entropy as shown in Eq. (6) and FFNNs is created. Classifier (Identifier) in this study has input, intermediate, output layer, respectively. The units in the network consist of 12,000, 10, and 6 units because the network is used for two preprocessing and we created classifiers using four, ten, six units in the input, intermediate, and output layer, respectively.

$$f(u) = \frac{1}{1+e^{-u}} \tag{3}$$

$$z_j = f\left(\sum_{i=0}^{n} w_{ji} x_i\right) \tag{4}$$

$$y_k = f\left(\sum_{j=0}^{m} v_{kj} z_j\right) \tag{5}$$

$$E = -\sum_{n=1}^{N}\sum_{k=1}^{K} d_{nk} log\left(y_{nk}\right) \tag{6}$$

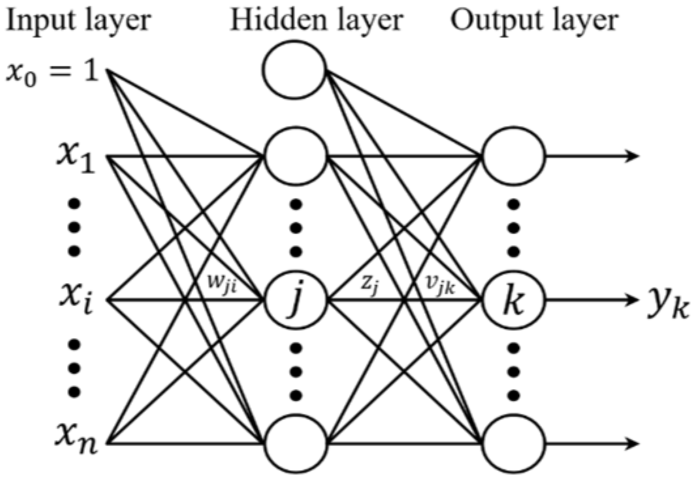

Fig. 6 - Feedforward neural network

2.5 Support Vector Machine

SVM (Support Vector Machine) is a machine learning model that is used for pattern recognition. SVM is often used as a problem solving method for a binary classification. Support vector is a feature vector which is selected in the learned vectors and we create the classifier using this support vector and a real number vector function called determination function. The margin is the distance between the support vector and the deterministic boundary. In SVM method, the deterministic boundary is created so that the margin becomes maximum as shown in Fig. 7. The meaning of linear SVM is based on the following a linear function as shown in Eq. (7). In Eq. (7), $\boldsymbol{x}$ means input vector, $\boldsymbol{w}$ means normal vector, and b means bias of determination value. The variables w, b can be obtained by using Lagrange Multiplier Method because they are the parameters when creating the determination function. In many cases, linear SVM treats linearly inseparable problem(s). Therefore, SVM is used using nonlinear kernel function. The input distribution which cannot be linearly separated changes to the distribution that the input can be linearly separated. We evaluate the use of radial basis function as shown in Eq. (8) as a kernel function. The determination function of nonlinear SVM is defined in Eq. (9). The input vector can change to the optimization problem called a dual problem by adding the dual variables $\alpha=(\alpha_1,\ldots,\alpha_n)$ as shown in Eq. (10).

In Eq. (8) to Eq. (10), $\boldsymbol{x}_i$ is i-th input vector of learning data, i-th data of y is $y_i \in \{-1,1\}$, C is a normalized parameter to allow misclassification. γ is the parameter to decide the gradient of kernel. n is a constant which shows the number of learning data. In this study, the parameters of C, γ were decided using a trial and error fashion. There are "One-Versus-Rest" and "One-Versus-One" in the multi-class classification methods. "One-Versus-Rest" has a feature that is easy to implement because it needs the learning of the number of classes using only two class classifiers. "One-Versus-One" is the way that the number of classifiers is the same as the number of the combination of each class are created and the identification (classification) results are output using the principle of decision by majority. In this study, six classes of classification using "One-Versus-One" method is used, so the combination of ${}_6C_2$ (=15) of the classifiers were created and the classification was done.

$$f(x) = \boldsymbol{w} * \boldsymbol{x} + b \tag{7}$$

$$K\left(\boldsymbol{x}_i, \boldsymbol{x}_j\right) = exp\left(-\gamma \left\|\boldsymbol{x}_i - \boldsymbol{x}_j\right\|^2\right) \quad (8)$$

$$f\left(\boldsymbol{x}\right) = \sum_{i\in[n]} \alpha_i y_i K\left(\boldsymbol{x}_i, \boldsymbol{x}_j\right) \quad (9)$$

$$\begin{aligned} &\max_{\alpha} -\frac{1}{2}\sum_{i,j\in[i]} \alpha_i \alpha_j y_i y_j K\left(\boldsymbol{x}_i, \boldsymbol{x}_j\right) + \sum_{i\in[n]} \alpha_i \\ &subject \quad to \quad \sum_{i\in[n]} \alpha_i y_i = 0 \\ &0 \le \alpha_i \le C, i \in [n] \end{aligned} \quad (10)$$

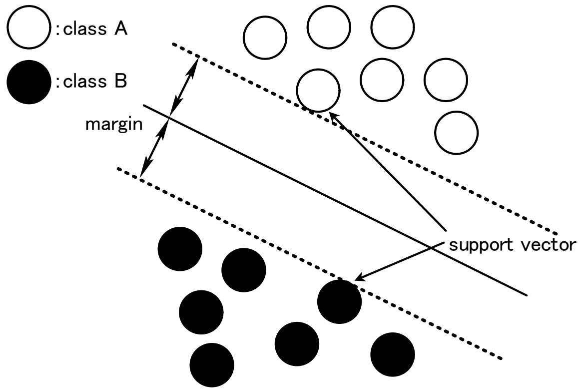

Fig. 7 - Support vector machine

2.6 Creation of Input Data

In this experiment, two patterns of input data set were created. The following was the creation of the input data set procedure. First of all, the processing of "normalized value of the maximum" for RMS was done and the data of four electrodes (3000 data) changed to 12,000 dimensions vector which was input data set. This data set is defined as RMS as shown in Fig. 8. Second, IEMG was created using RMS. After that, we took the rate of integration of the myoelectric potential and the input data set as four dimensions vector. This data set is defined as IEMG as shown in Fig. 9 and Eq. (11).

$$a' = \frac{a}{a+b+c+d} \quad (11)$$

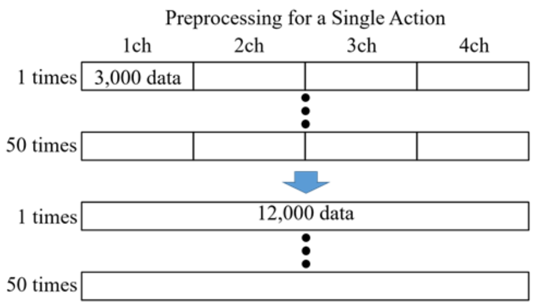

Fig. 8 - Preprocessing for RMS

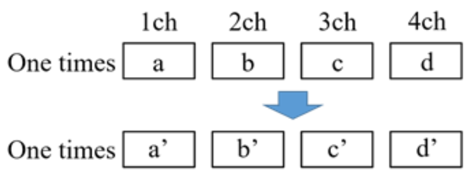

Fig. 9 - Preprocessing for IEMG

2.7 Experiment Procedure

The input data divided into five group per motion and we create five data sets. Using repeating for five times evaluation (cross-validation), so all five data sets become the evaluation data as shown in Fig. 10. Using the combination of two patterns of preprocessing methods (RMS, IEMG) and two classifiers (FFNNs, SVM), the creation of classifiers and the evaluation of motion identification were carried out. The patterns of combinations are "FFNNs+RMS", "FFNNs+IEMG", "SVM+RMS" and "SVM+IEMG" (four patterns). In the case of "FFNNs", the expression of each motion at the output layer is shown in Table 2 when learning is carried out. The evaluation of motion identification in the experiment is used for three evaluation indexes of "accuracy rate", "precision rate" and "recall rate".

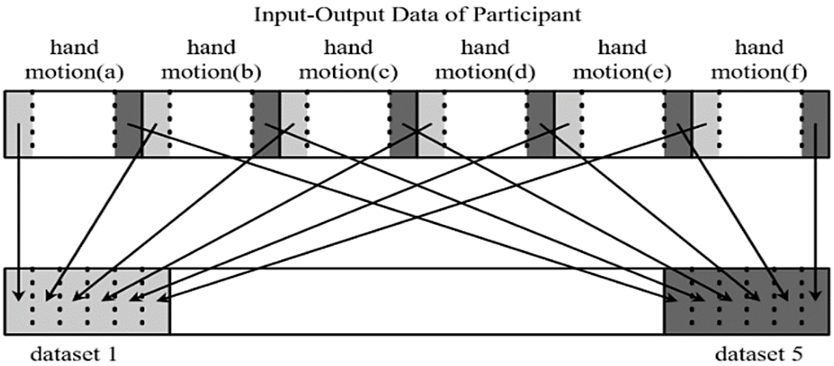

Fig. 10 - Method to build data set

Table 2 - Supervised Signals of FFNNs

Hand motion	Output of k-th neuron in the output layer					
	1	2	3	4	5	6
Relaxation	1	0	0	0	0	0
Grasping	0	1	0	0	0	0
Opening	0	0	1	0	0	0
Palmar flexion	0	0	0	1	0	0
Dorsal flexion	0	0	0	0	1	0
Ulnar flexion	0	0	0	0	0	1

3. Experimental Results

The results of accuracy in the case of using the proposed and conventional method are shown in Table 3 to 8. The results for the proposed and conventional methods are in Table 3 to 5 and Table 6 to 8, respectively. Using the proposed method that four electrodes are assigned (attached) at the middle of arm like a wrist band and the myoelectric potential is measured, the identification rate of more than 95% is shown. In addition, the improvement of the identification rate using the proposed method is 5% (maximum case, minimum improvement is approximately the same) compared with the conventional method.

Table 3 - Accuracy rate with proposed method [%]

Method \ Participants	A	B	C	D	E
FFNNs + RMG	96.3	95.7	98.3	96.0	97.7
FFNNs + IEMG	93.7	97.0	98.0	94.0	98.3
SVM + RMS	98.7	99.3	100	100	98.3
SVM + IEMG	94.7	96.0	99.0	93.7	99.0

Table 4 - Precision rate with proposed method [%]

Method \ Participants	A	B	C	D	E
FFNNs + RMG	95.2	95.3	98.0	96.0	97.1
FFNNs + IEMG	89.4	94.4	98.0	88.1	97.8
SVM + RMS	98.8	99.4	100	100	98.6
SVM + IEMG	95.6	96.4	99.1	94.7	99.1

Table 5 - Recall rate with proposed method [%]

Method \ Participants	A	B	C	D	E
FFNNs + RMG	97.4	95.6	98.7	97.0	98.1
FFNNs + IEMG	97.1	97.8	98.3	97.5	99.0
SVM + RMS	98.7	99.3	100	100	98.3

SVM + IEMG	94.7	96.0	99.0	93.7	99.0

Table 6 - Accuracy rate with conventional method [%]

Method \ Participants	A	B	C	D	E
FFNNs + RMG	93.3	94.0	88.7	97.3	85.3
FFNNs + IEMG	97.3	92.0	96.0	97.3	84.7
SVM + RMS	99.0	100	96.3	99.3	94.7
SVM + IEMG	97.7	91.3	96.0	96.7	85.0

Table 7 - Precision rate with conventional method [%]

Method \ Participants	A	B	C	D	E
FFNNs + RMG	91.9	92.5	85.2	96.5	84.6
FFNNs + IEMG	94.1	85.4	92.0	94.3	71.6
SVM + RMS	99.1	100	96.9	99.4	95.9
SVM + IEMG	97.7	92.4	96.4	97.0	87.4

Table 8 - Recall rate with conventional method [%]

Method \ Participants	A	B	C	D	E
FFNNs + RMG	96.6	94.6	95.5	98.3	86.5
FFNNs + IEMG	98.3	95.1	98.6	98.7	91.2
SVM + RMS	99.0	100	96.3	99.3	94.7
SVM + IEMG	97.7	91.3	96.0	96.7	85.0

4. Discussion

In this proposed method, the accuracy of identification is more than 95 %. The reason of the accuracy is shown in Fig. 11 and Fig. 12. They are the input vector of "RMS" and "IEMG" creating from the input data. The input vector's dimensions are reduced by using a main component analysis and they become the feature vector of two dimensions. In this study, the integrated EMG (IEMG) of fully added the RMS is used, and the feature quantity keeps in the IEMG because it shows in this feature map. Because of this, even though only RMS is done in the preprocessing, the motion classification can be done enough. In addition, SVM is a network model that is consist of one input, intermediate, output layer; that is to say, it is similar to the FFNNs in this study, so it is supposed that the similar results were obtained. The main reason of the improvement of the accuracy of classification is that the input vector can be linearly separated as shown in the results of this experiment.

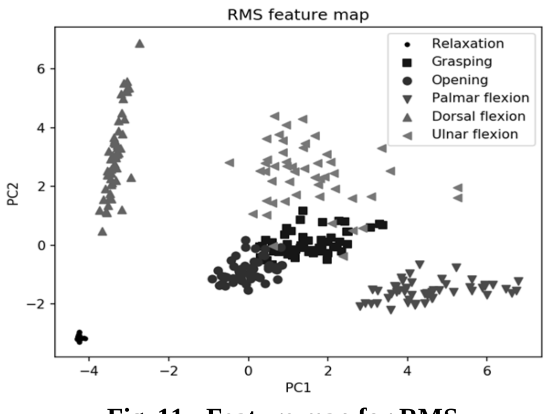

Fig. 11 - Feature map for RMS

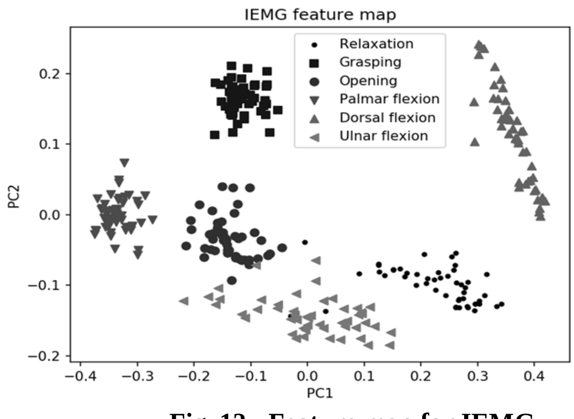

Fig. 12 - Feature map for IEMG

5. Conclusion

In this study, we propose the arrangement using simple method and the preprocessing way of the electrodes and the preprocessing way involved in doing it. The evaluation in the experiment shows the usefulness of proposed method. The evaluation shows almost the same accuracy compared with the conventional method. Because of this, it is supposed that the proposed method of the combination of the way that four electrodes are assigned (attached) at the middle of arm like a wrist band and the way that pretreatment (preprocessing) method using the ratio of the myoelectric potentials is useful. The results of the FFNNs and the SVM as the classifiers are almost the same, so it is supposed that there is no influence on the classifiers which is proposed. We will propose an arrangement of the electrodes mitigating in numbers using a simpler method. We will evaluate the usefulness of new arrangements. In addition, we will propose the improvement of classifier's three evaluation indexes of "accuracy rate", "precision rate" and "recall rate" based on the proposed method in the future.

References

[1] Mallik, S., & Dutta, M. 2017. A study on control of myoelectric prosthetic hand based on surface EMG pattern recognition. International Journal of Advance Research in Science and Engineering, 6(7), 635–646.

[2] Damodar, D. R., Suthar, U. V. & Solanki, H. D. 2018. Myo-electric hand: Prosthetic hand replication using EMG based approach. International Journal of Engineering Development and Research, 6(3), 658–662.

[3] Takala, E. P., & Toivonen, R. 2013. Placement of forearm surface EMG electrodes in the assessment of hand loading in manual tasks. Ergonomics, 56(7), 1159–1166.

[4] Rainoldi, A., MelchiorriI, G., & Caruso, I. 2004. A method for positioning electrodes during surface EMG recordings in lower limb muscles. Journal of Neuroscience Methods, 134(1), 37–43.

[5] Oskoei, M. A., & Hu, H. 2008. Evaluation of support vector machines in upper limb motion using myoelectric signal, 13th International Conference on Biomedicals and Bioengineering. National University of Singapore, Singapore. 176–181.

[6] Tsuji, T., Fukuda, O., Kaneko, M., & Ito, K. 2000. Pattern classification of time-series EMG signals using neural networks. International Journal of Adaptive Control and Signal Processing, 829–848.

[7] Bu, N., Fukuda, O., & Tsuji, T. 2013. EMG-based motion discrimination using a novel recurrent neural network. International Journal of Intelligent Information Systems, 21(2), 113–126.

[8] Kazuya, K., Kei, H., & Kiyotaka, K. 2020. Construction of myoelectric signal classifier using LSTM and efficacy of prior learning and relearning processes. Engineering Letters, 28(3), 668–675.