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An Evaluation on EMG-based Machine Learning Classification of Hand Movements Using Three Electrodes Arrangement on Forearm

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Abstract

A lot of types of myoelectric prosthetic hands using surface electromyogram have been investigated and developed in recent years. To control the myoelectric prosthetic hands, it is required to develop a high classification rate system. We propose a method of electrode placement and pretreatment by placing the three electrodes at the mid-forearm in the form of an armband. Even though similar studies have been developed in the past, we investigate the arrangement of electrodes among a lot of measurement points. To reduce the number of measuring electrodes, we evaluate the effects of muscle potential measurements on the pattern recognition and the classification of the useful measurement points by fixing three electrodes arranged in the form of armbands using the proposed method. As the results of experiments, we obtain that the combination of the preprocessing using the rates of myoelectric signals value and the measurement of myoelectric signals using the arrangement of three electrodes in an armband form and around the middle of the forearm is useful in the proposed method. Alternatively, the results have almost the same characteristics compared to the case of four electrodes. Lower cost and improvement of user convenience are achieved by the proposed method.

1. Introduction

In recent years, to use myoelectric prosthetic hands is one of the means which is easy for the people who were born without hands and arms or lost them after birth; moreover, their lives become more enriched [1][2]. According to a survey related to these people's inconvenience by the Ministry of Health, Labour and Welfare of Japan in 2022, the number of people with an upper limb disability is 533 thousand and many people want to use myoelectric prosthetic hands. Such people mainly use cosmetic prosthetic hands; however, their activities of daily life cannot conveniently be performed. So, it is expected the development of prosthetic hands acting by reflecting their own will and there are many studies being performed to develop myoelectric prosthetic hands. As for the people who lost their upper arms after birth, they have the feeling of movement of their missing hands and arms that it is called phantom limb. Because of this, myoelectric prosthetic hands are controlled by using occurring myoelectric signals when moving the phantom limb.

According to the previous studies, the arrangement methods are that the electrodes are attached at the major movement of the muscles of the arms of research subjects, and they use many electrodes [3][4]. So, it is convenient to obtain myoelectric signals. The preprocessing methods of the myoelectric signals are the frequency analysis, the integrated muscle potential, and the independent component analysis. The classifying methods are Decision Tree, K-Nearest Neighbor, Support Vector Machine (SVM) and Feedforward Neural Networks (FFNN) [5]-[8]. In the above consideration, the appropriate arrangement of the electrodes is necessary to control the myoelectric prostheses by using the myoelectric signals. Therefore, it is necessary to adjust the arrangement of the electrodes by the experts. Therefore, we propose a simple electrode arrangement method with a preprocessing. In this method, the electrodes are arranged in an armband form and around the middle of the forearm as shown in Fig. 1. Compared to the conventional electrode arrangements shown in Fig. 2, the proposed electrode arrangements have advantages of cost-effectiveness, reducing the processing burden, and convenience by adjusting the electrode arrangement without relying on experts. We determine the electrode arrangement based on the previous study. After that, the acquired myoelectric signals are smoothed to use pattern recognition; in addition, a preprocessing of the signals using the selected three points of the rates of myoelectric signals are performed. In the previous study, we evaluated in the case that the number of electrodes is four [9]. In this paper, we investigate and evaluate the case of the three electrodes. Reducing the number of electrodes for measuring is very useful for the person who should be attached to the body. In this study, we investigate the differences of the influence in the feature extracting and classifying methods by evaluation of the two methods of preprocessing of the signals (Root Mean Square, integrated muscle potential) and the rates of classification in the two classifying (SVM and FFNNs). In the cases we investigate, the number of electrodes is three and four.

2. Proposed Method

In this paper, we propose that the three electrodes are arranged in an armband form and around the middle of the forearm as shown in Fig. 1. The combination between the proposed method in which the three electrodes are arranged and the method using the rates of the myoelectric signal is very useful. Because of this, people who have no special knowledge can arrange the electrodes.

Table 1 *Measurement conditions*

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

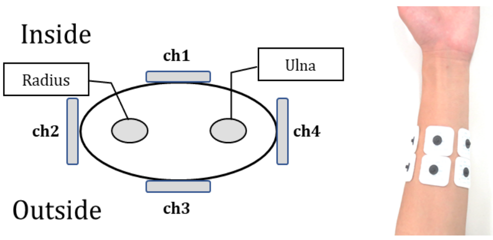


Fig. 1 *Proposal measurement position (using three electrodes such as channel 1,2, and 3)*

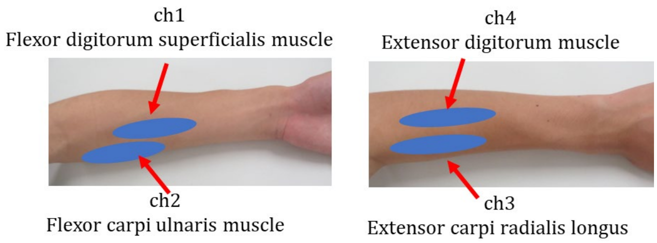


Fig. 2 *Conventional measurement position*

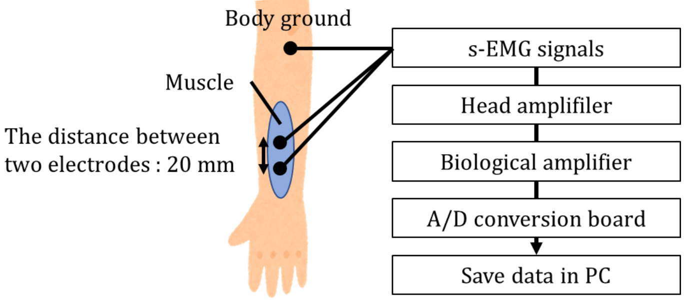


Fig. 3 *Measurement system*

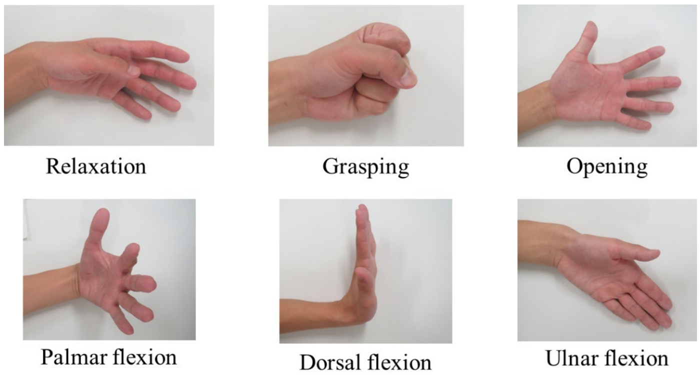


Fig. 4 *Hand motions*

3. Experimental Method

3.1 Myoelectric Signal

The myoelectric signal shows that the myoelectric potential occurs when a muscle fibre receives a motion command. The myoelectric signal recorded and displayed is called an "electromyogram." Because of this, it is considered that the electromyogram can be used to estimate the amputee's possible range of motion because of motion command information. To control the myoelectric prostheses, the processing of pattern recognition and obtaining the myoelectric signal with a high accuracy and recognizing ability is needed. The methods to obtain the myoelectric signal depending on the use of the electrode have two types; one is to use of a surface electrode attached to a skin surface called a method of electromyography (EMG). The thing recorded by using this method is called a surface EMG. The other method is to use of a needle electrode called a method of needle electromyography, and the thing recorded by using this method is called a needle EMG. In this study, the use of a non-invasive method (surface electromyography) is applied in terms of the use of motion analysis. In the experimental method, the method of surface EMG is used.

3.2 Myoelectric Signal Measurement

In this myoelectric signal measurement system, the myoelectric signal from the measurement point amplifies the signal by using a head amplifier and a biological amplifier; after that, the myoelectric signal is A/D converted and obtained as shown in Fig. 3. The experimenters are the five healthy men, and their age is 22 as shown in Table 1. It shows the contents of the experiment and we got their consent to cooperate as the subjects in advance. In addition, the conditions of the experiment are "amplifier gain: 74 dB", "A/D conversion: 16bit", "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." In this case, the six kinds of motions performed by the operation are "Relaxation," "Grasping," "Opening," "Palmar flexion," "Dorsal flexion," and "Ulnar flexion" as shown in Fig.4. The number of the electrode's arrangement is two in this case. The electrodes are arranged at the nearest position to each active muscle in a conventional manner as shown in Fig.2. On the other hand, the electrodes are arranged in an armband form and around the middle of the forearm in the proposed manner. In the experiment, the disposable electrodes are attached to the forearms in the above two manners; after that, the measurements are carried out using a bipolar recording method when acting for the specified six motions. The bipolar recording method has a body ground attached to the bone end part which has no influence of the voltage occurring by the measurement object. The method used is a body ground and two measurement points are applied, and we measure the voltage between the body ground and each measurement point. Because of this, the noise can be reduced in accurate measurement.

3.3 Preprocessing of Myoelectric Signal

The measured myoelectric signal extracts a feature quantity and identifies the motion information using the feature quantity. Frequency information is often used as the feature quantity; however, we use the processing of "root mean square (RMS)" and the post-processing of adding fully after RMS processing called "Integrated EMG(IEMG)". In Fig. 5, the first and second rows mean the measurement data and the absolute values of the data, and third rows mean RMS of the data, respectively.

3.3.1 Root Mean Square (RMS)

The value of "RMS" means that the myoelectric signals squared within a prescribed time range and the data is to find an average value and take the square root value (effective value) as shown in Eq. (1), where s(t) means "the myoelectric signals" and "*T*, *i*, and *k*" mean "calculation section, electrode position, and the hand motion," respectively. The effective value is calculated while shifting little by little the timing of the target section and the time variation of the effective value can be obtained. In this study, the calculation section is 41 msec and the effective value per 250 times of sampling period is calculated. The reason is that it can prevent an operator from feeling the time delay because there is 100 msec of the time until the force is generated on the muscle after the myoelectric signal occurs. So, considering the calculation of the identification processing time, we decide that the calculation section is 41 msec.

$$RMS_i^k(t) = \sqrt{\frac{1}{T}\int_0^T s_i^{k^2}(t+\tau)d\tau} \tag{1}$$

3.3.2 Integrated Electromyography (IEMG)

IEMG is an integrated value of rectified waveform during a certain period of time; that is to say, it means a total discharge amount. Generally, the signals multiply a coefficient (a forgetting rate) in the calculation of IEMG; after that, the signals are added. However, the integration of the value of RMS is IMEG in this study. In this case, the calculation of IEMG does not adopt such a usual method because the waveform adding the forgetting rate is similar to the result of the processing of RMS as shown in Eq. (2).

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

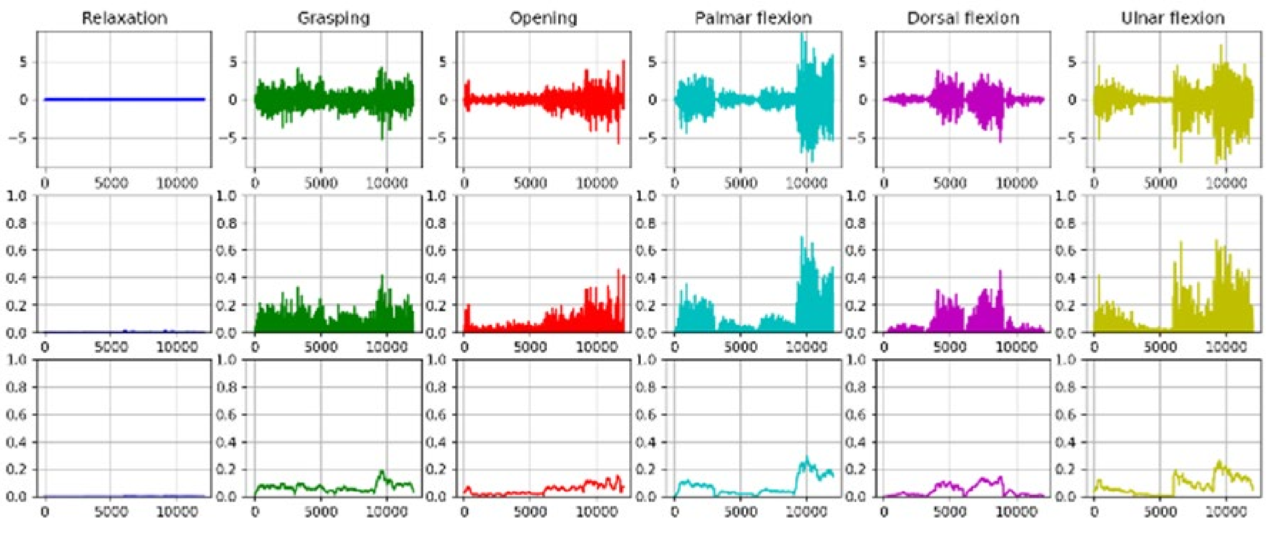


Fig. 5 *Scheme of preprocessing*

3.4 Feedforward Neural Networks

Feedforward Neural Networks (FFNNs) are composed of many neurons which arranged to form layers, and the neurons are connected to only the adjacent neurons; in addition, FFNNs are the networks that information used to propagate to the next neuron in one direction as shown in Fig. 6. Each unit for the inputting signals multiplies with the different weights and adds them each other; that is to say, one output is calculated, and its result propagates to the next layer. The result is multiplied with an activation function in reality. In this case, a sigmoid function is used as the activation function. The output of each unit is shown in Eqs. (4) and (5). The learning algorithm uses a "back propagation method" in this case. This method adjusts the weights of the neural network and minimizes the error function. The error function is calculated based on the difference between the teacher signal and output signal; in addition, FFNNs involve the error function using a cross-entropy error. The classifiers in the network are composed of the input, middle, and output layer. In this study, because the two preprocessing methods are used, one classifier using RMS method has the number of units is 9,000 for the input layer, 10 for the middle layer, and 6 for the output layer. The other classifier using IEMG method has the number of units of 3 for the input layer, 10 for the middle layer, and 6 for output layer.

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

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

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

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

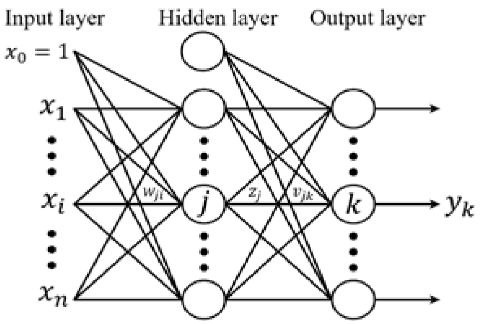


Fig. 6 *Feedforward neural network*

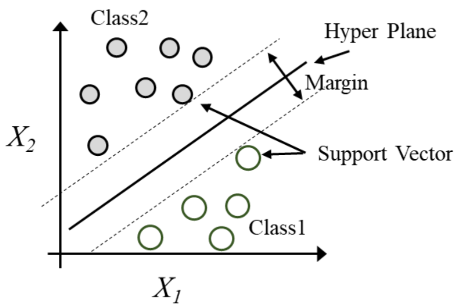


Fig. 7 *Support vector machine*

3.5 Support Vector Machine

SVM is a machine learning model used for pattern recognition. SVM is used for the method of solving the problem of binary classification. "Support vector" means the feature vector in the learning vector; moreover, the classifiers are made using this function and a real number function called the decision function. The margin is the distance between the support vector and decision boundary surface. The decision boundary surface is made so as to maximize the margin as shown in Fig. 7. The linear SVM method is based on the following Eq. (7) of a linear function. In the above equation, x, w, and b mean the input vector, the normal vector, and the bias of determination value, respectively. They are the parameters used when making the determination function because w and b can be calculated by "Lagrange Multiplier Method." However, linear SVM is a linear separable problem in many cases. Therefore, SVM using a non-linear kernel function is used. An input distribution which cannot be linearly separated that change to the input distribution which can be linearly separated by using the kernel function. In the case of applying a radial basis function as shown in Eq. (8) as the kernel function that is considered. The determination function of the non-linear kernel function is defined as shown in Eq. (9). It can be replaced by the optimization problem called a dual problem by adding the dual variables α=(α_1,...,α_n) as shown in Eq. (9).

In Eqs. (8) to (10), we assume that x_i, x, C, γ, and n are an input vector of i-th learning data, an element of the set {-1, 1}, a regularization parameter to permit misclassification, a parameter to decide the kernel gradient, a constant to express the number of learning data. In this case, the parameters of C and γ are decided in the manner of trial and error. The methods of multi-class classification are "One-Versus-Rest" and "One-Versus-One." The method of "One-Versus-One" has a good point of view of performing easily because of learning two classes of classifier (learning only the number of classes). The method of "One-Versus-One" is that it makes the classifiers for the number of the combination of each class and the classification result is outputted by using the principle of decision by majority. In this case, the method of "One-Versus-One" is used for six classes classification; so, ${}_6C_2$ (equals 15) combinations of classifiers are made and performed the classification.

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

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

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

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

4. Experiments and Results

4.1 Making the Input and Output Data

In this study, two patterns of the input and output data are made, and the experiment is performed. We explain the method of making the input and output data. First, the normalization for RMS processing is carried out by maximization; in addition, 3,000 data at three points (electrodes) as a 9,000-dimensional vector are made to input and output data. These data are defined as RMS (preprocessing for RMS) as shown in Fig. 8. Second, IEMG is calculated using RMS. After that, the ratio of integrated muscle potential at four-point electrodes can be obtained. Finally, the input and output data as a three-dimensional vector are made. These data are defined as IEMG as shown in Fig. 9 and Eq. (11).

4.2 Experiment Procedure

In the experiment, the input data are divided into five groups per each motion, and five data sets are made. In each motion, the four sets are the learning data, and the other set is the validation data; in addition, the five times calculations are repeated so that the fifth data set can be the validation data by using cross-validation method as shown in Fig. 10. The making of classification and the validation of the motion classification are carried out using the combination of the two patterns (RMS and IEMG) of preprocessing methods and the two classification methods (FFNNs and SVM). The combination patterns are "FFNNs+RMS", "FFNNs+IEMG", "SVM+RMS", and "SVM+IEMG." The learning is carried out such as that the expression of each motion in the output layer of FFNNs is shown in Table 2. The validation for the motion classification in this experiment is carried out by using three evaluation indexes of the accuracy rate, recall rate, and precision rate. In this case, the numbers of the electrodes using in the experiment are three and four.

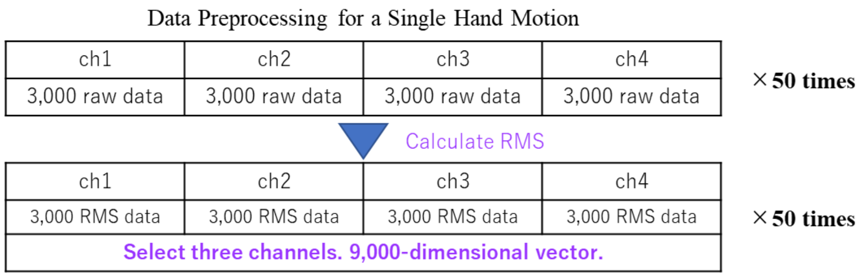


Fig. 8 *Preprocessing for RMS*

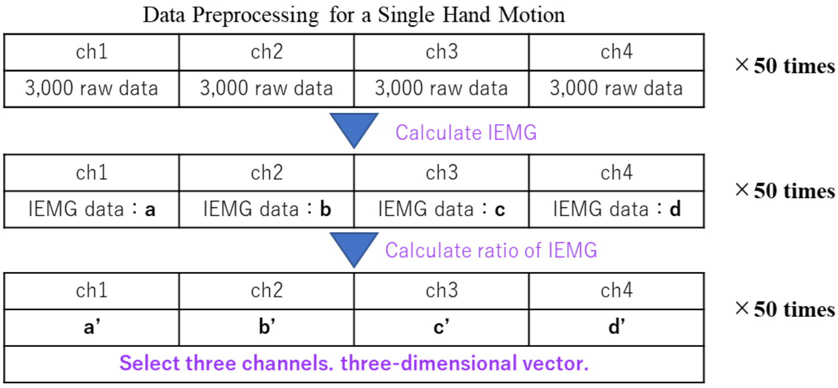


Fig. 9 *Preprocessing for IEMG*

$$a' = \frac{a}{a+b+c+d} \tag{11}$$

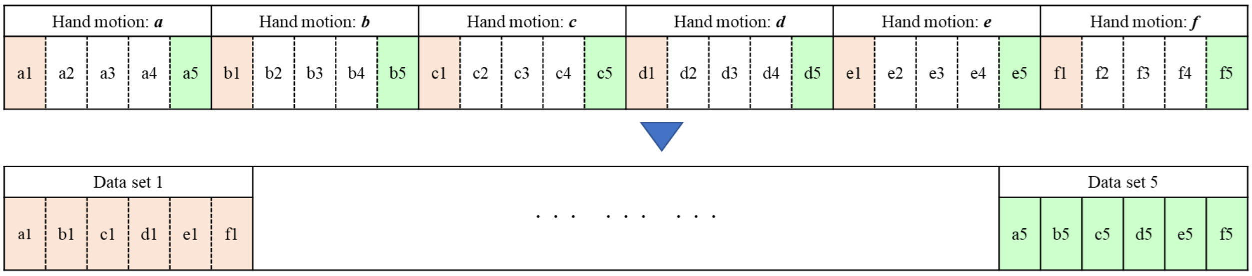


Fig. 10 *Method to build dataset*

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

5. Experimental Results

The classification rates in the case where the number of electrodes is reduced from four to three using the proposed and conventional methods are shown in the following tables. The results using four electrodes with the proposed and conventional methods are shown in Table 3 and Table 4 respectively [9]. The results using three electrodes with the proposed methods are shown in Table 5 to Table 8. In the case where the proposed method is used, the classification rates using four electrodes are 100.0% (maximum), 88.1% (minimum), and 97.2±2.4% (average). In the case of the conventional method, the classification rates using four electrodes are 100.0% (maximum), 71.6% (minimum), and 94.0±5.4% (average) [9]. In the case where the proposed method is used, the classification using three electrodes are 100% (maximum), 81.7% (minimum), and 95.9±3.1% (average).

Using the proposed method, when the number of electrodes is reduced from four to three, the simulation results in Tables 5 to 8 show an improvement in the classification rate of 1.9 percent and a decrease in its standard deviation from 5.4 to 3.2. In addition, there are no significant differences of classification rates among the combination of the channels (such as 123, 234, etc.) regarding the use of three electrodes as shown in Fig. 1. The results of classification rates are 90 percent or more in the case of any kinds of the combination of channels and the maximum differences are 2.7, 2.6, and 2.7 percent in the case of "Accuracy," "Precision," and "Recall," respectively.

Comparing the classification rates between the methods of FFNNs and SVM in the case of the proposed use of three electrodes, the results are 94.5 and 97.3 percent, respectively; that is to say, there are no significant difference between the two. Concerning the above results, the classification rate is effective even though using the proposed method in the case of three electrodes.

Table 3 *Result using four electrodes with proposal method* [%] [9]

Method \ Evaluation	Accuracy	Precision	Recall
FFNNs + RMS	96.8	96.3	97.4
FFNNs + IEMG	96.2	93.5	97.9
SVM + RMS	99.3	99.4	99.3
SVM + IEMG	96.5	97.0	96.5

Table 4 *Result using four electrodes with conventional method* [%] [9]

Method \ Evaluation	Accuracy	Precision	Recall
FFNNs + RMS	91.7	90.1	94.3
FFNNs + IEMG	93.5	87.5	96.4
SVM + RMS	97.9	98.3	97.9
SVM + IEMG	93.3	94.2	93.3

Table 5 *Result of FFNNs + RMS using three electrodes with proposal method* [%]

Participants \ Evaluation	Accuracy				Precision				Recall			
	123	**234**	**341**	**412**	**123**	**234**	**341**	**412**	**123**	**234**	**341**	**412**
A	89.6	95.4	93.3	94.5	88.7	95.2	92.7	93.5	91.2	96.1	94.0	94.8
B	91.9	95.4	92.0	94.3	91.1	94.8	91.4	93.4	92.5	95.8	92.7	95.1
C	97.7	97.6	94.9	95.2	96.8	96.3	94.4	94.0	98.3	98.3	95.3	95.6
D	94.8	95.9	93.1	94.9	93.8	94.9	92.3	94.0	95.4	96.3	93.6	94.9
E	96.5	94.5	92.0	92.6	96.0	93.4	90.5	91.2	97.0	94.9	92.5	93.6
Average	94.1	95.8	93.1	94.3	93.3	94.9	92.3	93.2	94.9	96.3	93.6	94.8
Average	94.3				93.4				94.9			

Table 6 *Result of FFNNs + IEMG using three electrodes with proposal method* [%]

Participants \ Evaluation	Accuracy				Precision				Recall			
	123	**234**	**341**	**412**	**123**	**234**	**341**	**412**	**123**	**234**	**341**	**412**
A	92.1	93.8	92.7	92.3	86.1	88.5	88.2	85.5	96.7	97.5	96.7	96.6
B	93.3	96.3	96.3	96.8	86.4	93.8	91.9	90.7	97.4	97.5	98.3	97.8
C	98.3	97.7	94.5	98.5	97.7	97.2	87.4	97.9	98.8	98.3	97.8	99.4
D	93.3	93.8	93.5	92.6	84.5	87.8	86.2	81.7	96.5	97.5	97.3	98.0
E	97.9	97.9	98.5	98.4	97.3	96.9	97.5	97.6	99.0	98.7	98.9	99.0
Average	95.0	95.9	95.1	95.7	90.4	92.8	90.2	90.7	97.7	97.9	97.8	98.1
Average	95.4				91.0				97.9			

Table 7 *Result of SVM + RMS using three electrodes with proposal method* [%]

Evaluation / Participants	Accuracy				Precision				Recall			
	123	**234**	**341**	**412**	**123**	**234**	**341**	**412**	**123**	**234**	**341**	**412**
A	97.0	98.7	96.0	95.7	97.5	98.8	96.9	95.9	97.0	98.7	96.0	95.7
B	99.0	97.7	95.0	96.7	99.1	97.8	95.4	96.9	99.0	97.7	95.0	96.7
C	100	100	100	97.0	100	100	100	97.3	100	100	100	97.0
D	99.7	100	99.7	97.7	99.7	100	99.7	98.0	99.7	100	99.7	97.7
E	97.7	98.0	95.0	96.0	98.1	98.2	95.8	96.7	97.7	98.0	95.0	96.0
Average	98.7	98.9	97.1	96.6	98.9	99.0	97.6	97.0	98.7	98.9	97.1	96.6
Average	97.8				98.1				97.8			

Table 8 *Result of SVM + IEMG using three electrodes with proposal method* [%]

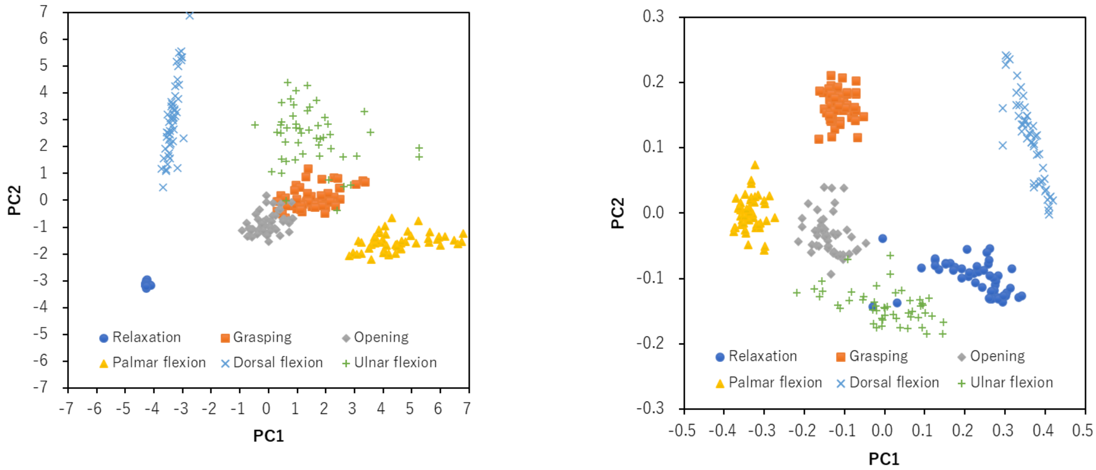
Evaluation / Participants	Accuracy				Precision				Recall			
	123	**234**	**341**	**412**	**123**	**234**	**341**	**412**	**123**	**234**	**341**	**412**
A	94.0	94.7	95.3	93.3	95.1	95.5	96.1	94.7	94.0	94.7	95.3	93.3
B	95.7	96.3	96.3	97.0	96.0	96.6	96.9	97.5	95.7	96.3	96.3	97.0
C	99.0	98.7	99.0	98.7	99.1	98.8	99.1	98.8	99.0	98.7	99.0	98.7
D	94.3	94.0	93.3	93.3	95.2	95.0	94.5	94.2	94.3	94.0	93.3	93.3
E	99.0	98.7	99.0	99.0	99.1	98.8	99.1	99.1	99.0	98.7	99.0	99.0
Average	96.4	96.5	96.6	96.3	96.9	96.9	97.1	96.9	96.4	96.5	96.6	96.3
Average	96.4				97.0				96.4			

6. Discussion

In the proposed method, when the number of electrodes is reduced from four to three, the overall average classification rate (Accuracy, Precision, and Recall) is 95.9% ± 3.1%. This is a slight improvement compared to the overall average classification rate of 94.0% ± 5.4% when using four electrodes with conventional methods. Additionally, we clearly showed that the six motions can be classified when using three electrodes.

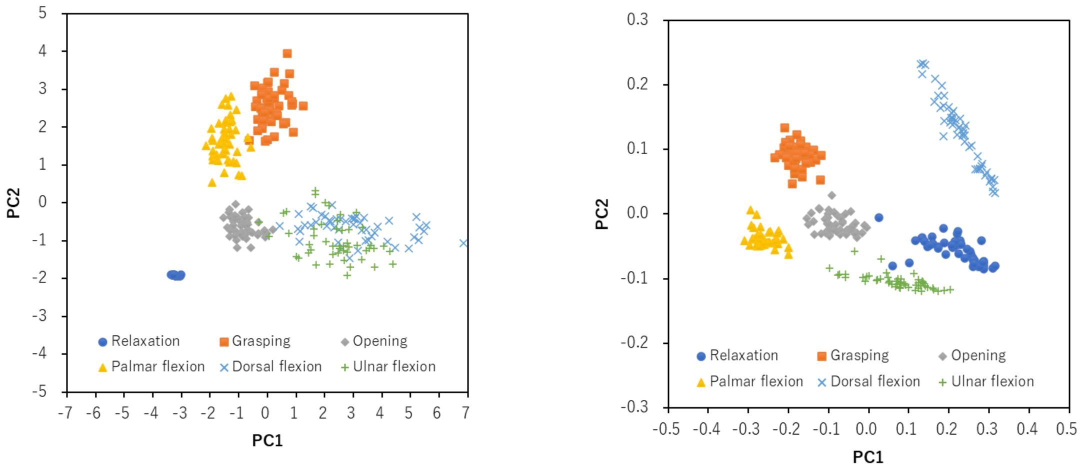
The results of principal component analysis using the proposed method with four and three electrodes are shown in Fig. 11 and Figs. 12 to 15, respectively, which provide the reasons for the improved performance mentioned above.

In the above results, three channels (ch1, ch2, and ch3 such as 123) (three electrodes) are selected from the four channels in Fig.1. From these results of the analysis, it is found that these two feature vectors can be separated linearly per each motion. In this study, IEMG is a full addition of RMS. In general, the feature quantity can be obtained by the processing of IEMG. However, it is found in Fig. 12 that RMS keeps the motion's feature before the processing of IEMG. Because of this, assuming that only the preprocessing for RMS is carried out, the feature vector can be sufficiently used for the motion classification. In addition, SVM is a network model which has the input (one), middle (one), and output (one) layer in the two classifiers. On the other hand, FFNNs (input (one), middle(one), and output(one) layer) is a perceptron model; so, it is considered that the similar results can be obtained because these are the similar networks. Therefore, the reason for such accuracy depends on the way to be able to separate linearly when the number of electrodes is reduced from four to three using the proposed method.



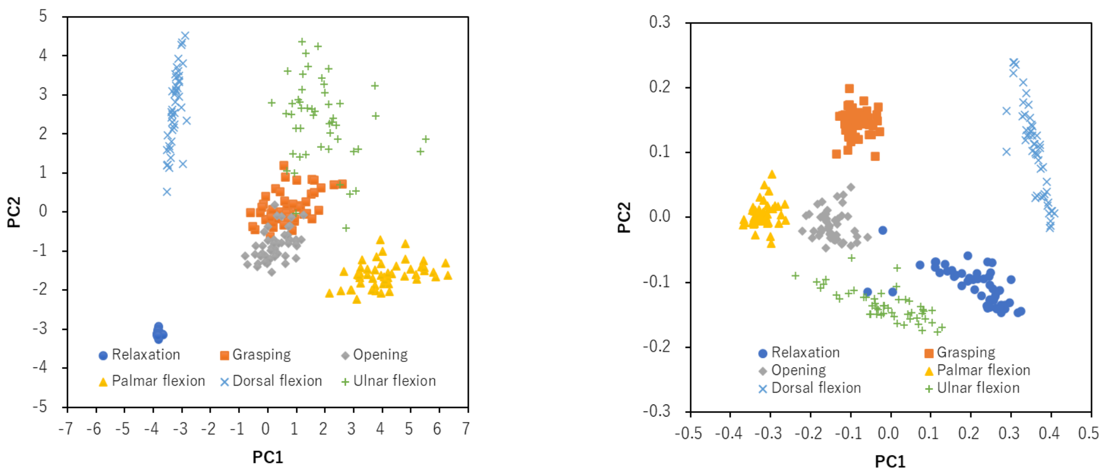
(a) **(b)**

Fig. 11 *(a) RMS feature map with all 4ch; (b) IEMG feature map with all 4ch*



(a) **(b)**

Fig. 12 *(a) RMS feature map with 3ch (123); (b) IEMG feature map with 3ch (123)*



(a) **(b)**

Fig. 13 *(a) RMS feature map with 3ch (234); (b) IEMG feature map with 3ch (234)*

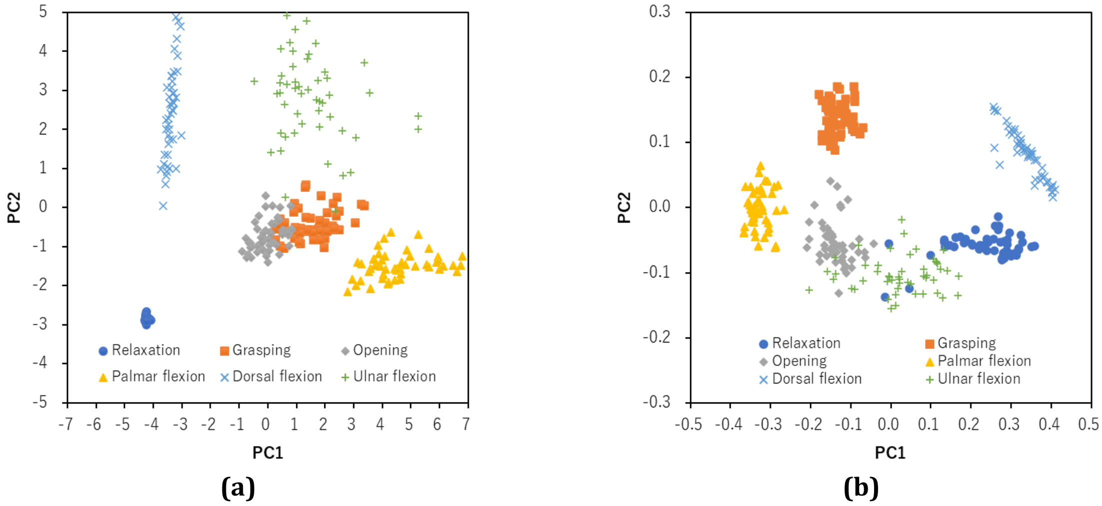


Fig. 14 *(a) RMS feature map with 3ch (341); (b) IEMG feature map with 3ch (341)*

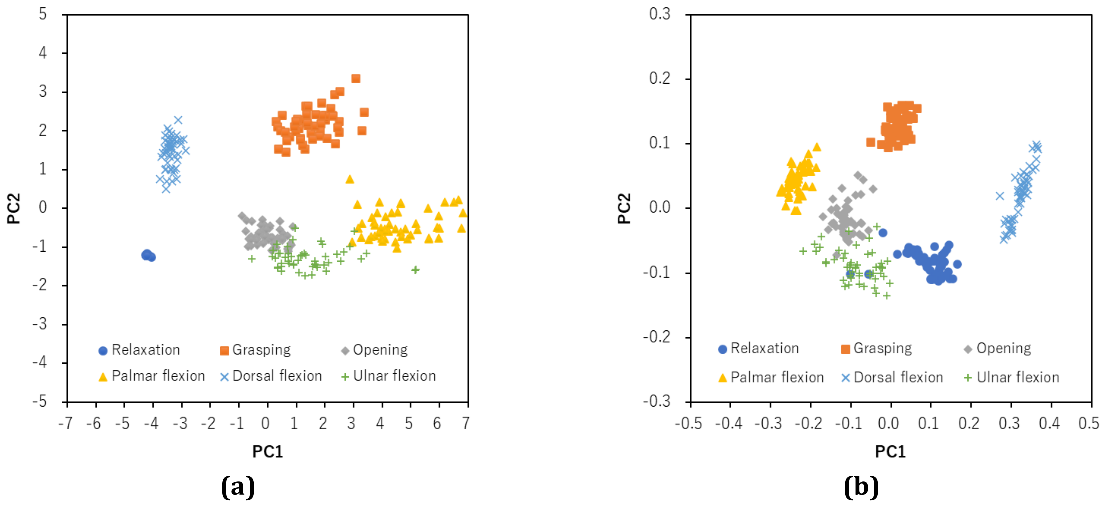


Fig. 15 *(a) RMS feature map with 3ch (412); (b) IEMG feature map with 3ch (412)*

7. Conclusion

In this study, we propose a simple electrode arrangement method (three electrodes) with a preprocessing using the rates of myoelectric signals value and evaluate the effectiveness of the proposed method. The experimental results show that the high classification rate can be more easily obtained using the proposed method compared than the conventional electrode arrangements. The combination of the preprocessing using the rates of myoelectric signals value and the measurement of myoelectric signals using the arrangement of three electrodes in an armband form and around the middle of the forearm is useful in the proposed method. Alternatively, the results of FFNNs and SVM have almost the same characteristics compared to the case of four electrodes; so, there is no influence on the classifiers when using the proposed method. Reducing the number of electrodes has advantages in terms of its cost effectiveness and processing burden. We will propose an arrangement of the electrodes mitigating in numbers using a simpler method, consider the effectiveness, and improve the accuracy rate, recall rate, and precision rate by composing of the classifiers using the proposed method as the future work. In addition, we will evaluate in the case where the electrodes are arranged at equal intervals.

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Conflict of Interest

The authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors are responsible for the study conception, research design, data collection, data analysis, result interpretation and manuscript drafting.

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