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Construction of Classifier of Myoelectric Signals by using ANNs

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Abstract—**Studies concern the myoelectric prosthetic hand that is controlled by using the myoelectric signals. Recent studies propose the methods of using the machine learning so as to construct the classifier that classifies the myoelectric signals. However, the machine learning needs a lot of learning data from the user to construct the classifier which classifies the myoelectric signals correctly. This traditional method places a large burden on the user for constructing the classifier. In this study, we consider the Feedforward Neural Networks and Recurrent Neural Networks to construct the classifier using non-user ' s myoelectric signals. In order to show the validity of our methods, we perform some experiments to classify the myoelectric signals and discuss the results of experiments in point of accuracy rate, precision rate and recall rate.**

Index Terms—**Feedforward Neural Networks, Recurrent Neural Networks, Support Vector Machine, Myoelectric Signals, Myoelectric Prosthetic Hand.**

I. Introduction

Many studies on the myoelectric prosthetic hand for people who lost their movement function due to an accident or illness have been published in recent years [1]-[3]. An myoelectric hand refers to an electric artificial hand that controls the movement by estimating the user's intention from the weak electrical signals (hereinafter the myoelectric signals) generated by the activity of the remaining muscles. Although, it is necessary to practice in order to move the myoelectric prosthetic hand along user's intention. The quality of life can be improved for the user by using the myoelectric prosthetic hand. Therefore, we think that it is worth using the myoelectric prosthetic hand. In recent studies, the methods of using the machine learning so as to construct the classifier that classifies the myoelectric signals have been proposed [3]-[5]. However, the myoelectric signals have individual differences, noises are loud, and the myoelectric signals change slightly even in the same repeated action of the user. Furthermore, a lot of learning data of the user are needed to construct the high accuracy classifier system. So we think that the traditional method places a large burden on the user for constructing the classifier.

In this paper, as the aim of reducing user's burden, we consider that the methods construct the classifiers using non-user's myoelectric signals. The considered methods deal with Feedforward Neural Networks (FFNNs) and Recurrent Neural Networks (RNNs) in Artificial Neural Networks (ANNs) for constructing the classifier. We think that our methods make it possible to construct the classifier which has the generality by compensating between the user's differences of the myoelectric signals. Therefore, it can be expected to construct the classifier by using a smaller number of user's learning data than those the traditional method needs. And the constructed classifiers by ANNs can be relearned using new learning data and be adjusted for the user through the relearned process. Furthermore, we construct the classifier which uses Support Vector Machine (SVM) in additional to the above two methods using ANNs. We perform some experiments in order to show the validity of our considered methods. We evaluate the constructed classifiers in point of accuracy rate, precision rate and recall rate, and discuss our findings.

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II. Myoelectric Signals and Measurement

A. Myoelectric Signals

When the brain transmits the command signals to muscle fibers, the myoelectric signals are generated. Generally, the inside of cell membrane at muscle fibers, has approximately -80 mV as potential compared with the outside. This potential reverses as a result of depolarization that occurs by receiving the command signals from the brain. The reversal potential, called action potential, propagates along muscle fibers interactively. This action potential is called electromyogram (EMG) [6].

There are two ways to measure the myoelectric signal. One is the needle EMG method. In this method, there is invasiveness to the human body. Nevertheless, the needle EMG method is applied to clinical department [6] because this method enables to recognize changes of the myoelectric signals with high spatial resolution. The other is the surface EMG method which measures the myoelectric signals from electrodes placed on the skin surface. This method has low invasiveness. Moreover, attaching and detaching electrode are easy. Also, the frequency range of surface EMG is about 5∼500 Hz [7].

B. Measurement of Myoelectric Signals

We applied the surface EMG method because of less physical burden. Five healthy adult male participants performed six hand motions (Fig. 1) for relaxation, grasping, opening, palmer flexion, dorsal flexion and ulnar flexion. Then, we obtained the myoelectric signals from four measurement positions (Fig. 2) which were flexor digitorum superficialis muscle (FDS), flexor carpi ulnaris muscle (FCU), extensor carpi radialis longus muscle (ECRL) and extensor digitorum communis muscle (EDC). Participants began performing a hand motion at the same time as sign to start measuring, and we measured the myoelectric signals. The bipolar measurement by using two disposable electrodes was applied. In this method, two electrodes are arranged on each measurement position. In addition, body earth is arranged on position such as a joint that is not affected by potential of measurement position. This method enables noises to decrease since those of both electrodes cancel each other. Two electrodes of a pair were arranged with a distance of 2 cm. The myoelectric signals were measured at a sampling frequency of 6000 Hz for 500 ms. So we obtained the myoelectric signals data having time-series length of 3000. We took the frequency range of the myoelectric signals and utility frequency range into consideration. Thus, the myoelectric signals were cut off the frequency range of less than 5 Hz, 59.5∼60.5 Hz, and more than 1000 Hz by digital filter of MATLAB after obtaining data. Participants reduced electric impedance of the skin to less than 5 kΩ by skin treatment before the measurement. Figure 3 and TABLE I show measurement system and measurement conditions, respectively.

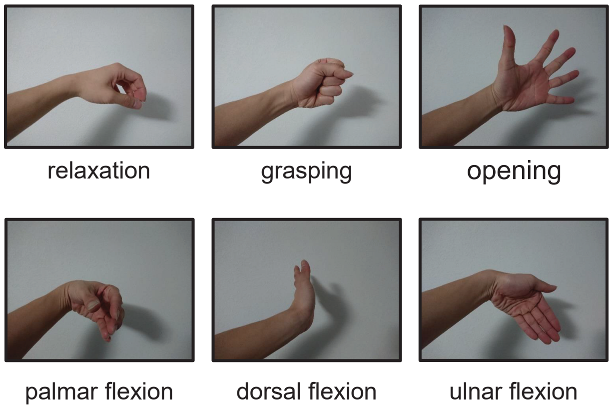

Fig. 1. Classified six hand motions

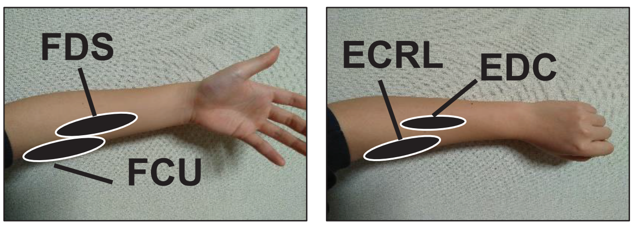

Fig. 2. Measurement positions

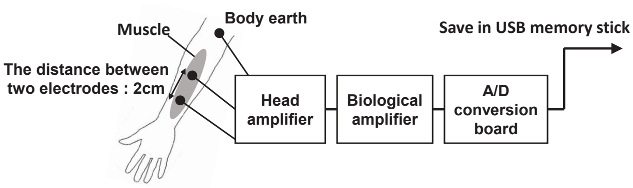

Fig. 3. Measurement system

III. Classifier and The Learning Algorithm

A. FFNNs and Learning Algorithm

FFNNs are composed of layers, each having some neurons. Each neuron connects to the neurons of the next layer. A weighted signal moves in one direction from the input layer to the output layer. FFNNs having three layers are shown in Fig. 4.

TABLE I
Measurement conditions

Head amplifier	BA-U001
Biological amplifier	BA-1008 Electrodes : Disposable electrode Gain : 74 dB
A/D conversion board	ADA16-32/2(CB)F
Sampling frequency	6000 Hz
Sampling time	500 ms
Filter	High-pass filter : 5 Hz Low-pass filter : 1000 Hz Notch filter : 50.5∼60.5 Hz
Electric impedance of the skin	less than 5 kΩ
Participants	Two 21-year-old males Three 22-year-old males

The equations for the outputs of each hidden layer neuron and output layer neuron are, respectively, given as

$$z_j = f(\textstyle\sum_{i=0}^{n} w_{ji} x_i) \tag{1}$$

$$y_k = f(\textstyle\sum_{j=0}^{m} v_{kj} z_j) \tag{2}$$

where x_i is the input variable from the i-th neuron in the input layer, z_j is the output variable of the j-th neuron in the hidden layer, y_k is the output variable of the k-th neuron in the output layer, w_{ji} is the weight between the i-th neuron in the input layer and j-th neuron in the hidden layer, v_{kj} is the weight between the j-th neuron in the hidden layer and k-th neuron in the output layer, and n and m are constants, which are the numbers of input layer neurons and hidden layer neurons, respectively. Moreover, $f(u)$ is the activation function given by the following equation.

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

The backpropagation (BP) is applied as learning algorithm. BP adjusts weights of network so that the error function E (Eq. (4)) is minimized. The error function indicates error between the calculated output and the supervised signal. According to the BP algorithm, v_{kj} and w_{ji} are adjusted by Eqs. (5) and (6)

$$E = \textstyle\sum_k (d_k - y_k)^2 \tag{4}$$

$$v_{kj}(t+1) = v_{kj}(t) - \eta \frac{\partial E}{\partial v_{kj}} \tag{5}$$

$$w_{ji}(t+1) = w_{ji}(t) - \eta \frac{\partial E}{\partial w_{ji}} \tag{6}$$

where, t is the number of iterations, d_k is the supervised signal of the k-th neuron in the output layer, and η is the learning rate.

The classifier constructed by FFNNs consisted of three layers: an input layer, a hidden layer and an output layer. Except for neuron assigned bias, the input layer had four neurons, the hidden layer had 50 neurons, and output layer had six neurons.

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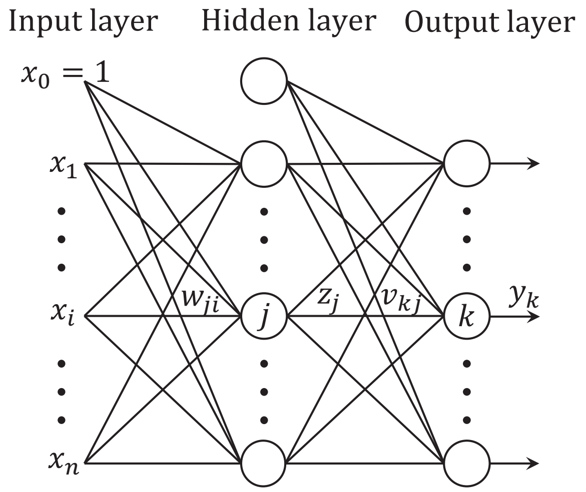

Fig. 4. Feedforward Neural Networks (FFNNs)

B. RNNs and Learning Algorithm

RNNs are able to handle time-series data. As a point of difference with FFNNs, the input values to hidden layer, are not only weighted signals from the input layer, but also weighted signals from the previous hidden layer (Fig. 5). With this structure, the past input influences output. RNNs are able to capture contextual characteristics of time-series data.

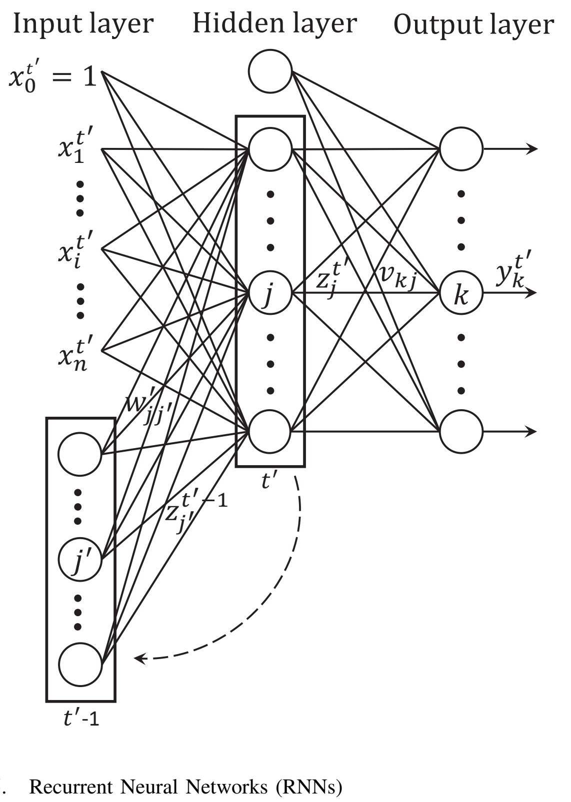

Fig. 5. Recurrent Neural Networks (RNNs)

The equation for the outputs of each hidden layer neuron and output layer neuron are, respectively, given as

$$z_j^{t'} = f(\textstyle\sum_{i=0}^{n} w_{ji} x_i^{t'} + \sum_{j'=0}^{m} w'_{jj'} z_{j'}^{t'-1}) \tag{7}$$

$$y_k^{t'} = f(\textstyle\sum_{j=0}^{m} v_{kj} z_j^{t'}) \tag{8}$$

where $x_i^{t'}$ is the input variable from the i-th neuron at time step t' in the input layer, $z_j^{t'}$ is the output variable of the j-th neuron at time step t' in the hidden layer, $y_k^{t'}$ is the output of the k-th neuron at time step t' in the output layer, $w'_{jj'}$ is the weight between the j-th neuron in the hidden layer at time step $(t'-1)$ and the j-th neuron in the hidden layer at time step t'.

The backpropagation through time (BPTT) is applied as learning algorithm. In the BPTT, RNNs develop in the time axis direction. BPTT adjusts the weight so that error function E (Eq. (9)) is minimized. The adjustments of the weight between the input layer and the hidden layer, and the weight between the hidden layer and the output layer, are the same as FFNNs. According to the BPTT algorithm, $w'_{jj'}$ is adjusted by Eq. (10).

$$E = \frac{1}{TN} \textstyle\sum_{t'=0}^{T} \sum_{k=0}^{N} (d_k^{t'} - y_k^{t'})^2 \tag{9}$$

$$w'_{jj'}(t+1) = w'_{jj'}(t) - \eta \frac{\partial E}{\partial w_{jj'}} \tag{10}$$

where $d_k^{t'}$ is the supervised signal of the k-th neuron at time step t' in the output layer, N is the constant which is the number of output layer neurons and T is the constant which is time-series length of input value $x_i^{t'}$.

However, RNNs are unable to handle long time-series data because of vanishing gradient of error function. Actually, the length that input influences output, is approximately 10 time steps. Therefore, we applied Long Short-Term Memory (LSTM) which enables input to influence output for a long time steps.

The classifier constructed by FFNNs consisted of three layers: an input layer, a hidden layer and an output layer. Except for neuron assigned bias, the input layer had four neurons, the hidden layer had 50 neurons, and the output layer had six neurons.

C. Support Vector Machine

SVM is a learning model of pattern recognition. SVM is applied as a solution of a binary classification problem. Support vectors are feature vectors chosen from learning data defines decision function. The margin is the distance between support vectors and classification boundary that classifies into two classes. SVM establishes classification boundary so that the margin is maximized (Fig. 6).

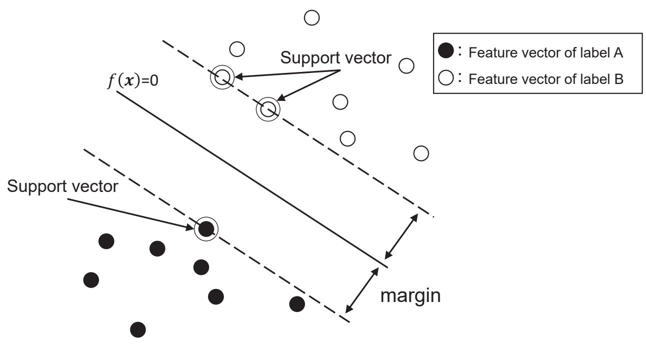

Fig. 6. Classification boundary and margin in SVM

The equation for decision function of linear SVM is defined as

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$$f(\boldsymbol{x}) = \boldsymbol{w} \cdot \boldsymbol{x} + b \tag{11}$$

where $\boldsymbol{x}$ is input vector, $\boldsymbol{w}$ is normal vector of classification boundary and b is an intercept of decision function. $\boldsymbol{w}$ and b are parameters to shape decision function. These parameters are found by the method of Lagrange multipliers. However, there is a limit to what linear SVM classifies linearly inseparable input. Therefore, nonlinear SVM by using Kernel function (Eq. (12)) is introduced. This SVM makes it possible to recognize linearly inseparable input. Kernel function converts linearly inseparable input distribution into linearly separable input distribution. Decision function of nonlinear SVM is defined as Eq. (13). The dual variable $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_n)$ is found by the optimization problem, which is called dual problem (Eq. (14)), to define decision function.

$$K(\boldsymbol{x_i}, \boldsymbol{x_j}) = exp(-\gamma ||\boldsymbol{x_i} - \boldsymbol{x_j}||^2) \tag{12}$$

$$f(x) = \textstyle\sum_{i \in [n]} \alpha_i y_i K(x_i, x) + b \tag{13}$$

$$\begin{aligned} \max_{\boldsymbol{\alpha}} -\frac{1}{2} \textstyle\sum_{i,j \in [n]} \alpha_i \alpha_j y_i y_j K(x_i, x_j) + \textstyle\sum_{i \in [n]} \alpha_i \\ subject \quad to \quad \textstyle\sum_{i \in [n]} \alpha_i y_i = 0 \\ 0 \leq \alpha_i \leq C, i \in [n] \end{aligned} \tag{14}$$

where γ is the hyper parameter to decide gradient of Kernel, $\boldsymbol{x_i}$ is input vector of i-th learning data, y_i is a label of i-th learning data which consists of $y_i \in \{-1, 1\}$, C is the regularization parameter to permit misclassification and n is the constant which is the number of learning data.

In SVM, the multi-class classification is made by combining some two-class classifiers. This study applied One-Versus-One as a method of multi-class classification. In this method, two-class classifiers are used as the number of combination of classes. Then, each two-class classifier learns regarding each combination of classes.

IV. Experiments to Classify Myoelectric Signals

A. Making of Input-output Data

The amplitude of the myoelectric signals changes depending on the force of squeezed muscle. Maximal Voluntary Contraction (MVC) is the muscle strength which a human maximizes contracting one's muscle intendedly and voluntarily. The amplitude and wave density of the myoelectric signals increase with an increase of muscle load. There is linear relationship between muscle activity and muscle load within 10∼90 % of MVC. In this study, time-integration was applied as feature variables.

Integration value was applied as input data of FFNNs and SVM. To make this value, we summed up absolute values of each myoelectric signals data obtained from four measurement positions within 500 ms (3000 plots).

The equation for input value x_i^k obtained from a measurement position i (i=1,...,4) (Fig. 2) in a hand motion k (k=a,...,f) (Fig. 1) was given as

$$x_i^k = \textstyle\sum_{n=1}^{3000} |Data_i^k(n)| \tag{15}$$

where $Data_i^k(n)$ is the value of n-th plot from a measurement position i in a hand motion k.

In making of input data, firstly, we divided the myoelectric signals of 500 ms (3000 plots) into 20 parts; each part has the myoelectric signals of 25 ms (150 plots). Then, each part was time-integrated within 25 ms (150 plots).

The equation for input value $x_i^k(t)$ of input i and time step t in a hand motion k was given as

$$x_i^k(t) = \textstyle\sum_{n=1}^{150} |Data_i^k(n)| \tag{16}$$

TABLE II shows each supervised signal, for FFNNs and RNNs, of six neurons in the output layer to each hand motion.

TABLE II
The Supervised Signal of FFNNs and RNNs

Hand Motion	Output of k-th neuron in the output layer					
	1	2	3	4	5	6
(a) Relaxation	0	0	0	0	0	1
(b) Grasping	0	0	0	0	1	0
(c) Opening	0	0	0	1	0	0
(d) Palmar Flexion	0	0	1	0	0	0
(e) Dorsal Flexion	0	1	0	0	0	0
(f) Ulnar Flexion	1	0	0	0	0	0

In this study, we obtained input-output data from five participants. We obtained 50 input-output data for each hand motion from each participant, so that the number of each participant's input-output data was 300. Consequently, 1500 input-output data were obtained from five participants.

B. Experiment I

In Experiment I, we made five participants' input-output data into five data sets. By using four data sets as learning data, we constructed classifier of FFNNs, RNNs and SVM. Then, we evaluated each constructed classifier using remaining one data set as evaluation data. The processing flow to make five data sets was as follows:

[Step 1] Extract 10 input-output data in each hand motion from each participant's 50 input-output data to make data set 1 which is stored a total of 300 input-output data.

[Step 2] Extract 10 input-output data, which is not used in [Step 1], in each hand motion from each participant's remaining 40 input-output data to make data set 2 which is stored a total of 300 input-output data.

[Step3] Repeat [Step 2] to make data set 3∼5.

Figure 7 shows the method to make data set 1.

5-fold-validation was applied as evaluation method. In FFNNs and RNNs of the Experiment I, the epoch was 3000, and learning rate was 0.005. Also, the learning rate of RNNs was changed automatically by applying the algorithm Adam [8]. The parameters of SVM were C=10 and γ=10.

TABLE III shows the average results of five fold in Experiment I. As the results, accuracy rate, precision rate and recall rate were more than 90 % in all three classifiers: FFNNs, RNNs and SVM. In particular, The classifier by using RNNs achieved high discrimination performance. We considered that RNNs model could acquire time-series variation of the myoelectric signals as feature variable from input data by

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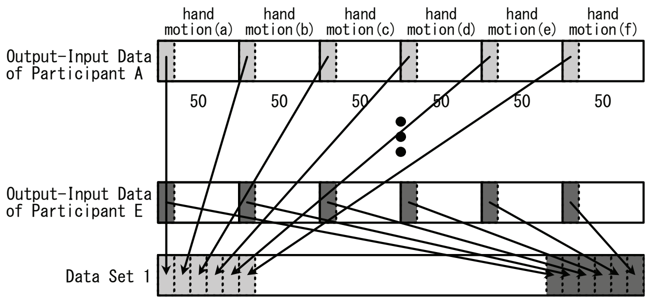

Fig. 7. The method of making data set 1

TABLE III
THE RESULTS OF EXPERIMENT I

Evaluation Items	Accuracy[%]	Precision[%]	Recall[%]
FFNNs	91.2	91.4	91.2
RNNs	93.8	93.8	93.8
SVM	90.7	90.8	90.6

handling the locally divided myoelectric signals data as time-series data.

C. Experiment II

Experiment II was performed to discuss generality of the classifier constructed by using non-myoelectric prosthetic hand user's learning data. We used four participants' input-output data as learning data to construct each classifier. Moreover, we evaluated each constructed classifier by using remaining one participant's input-output data as evaluation data. In FFNNs and RNNs of Experiment II, the epoch was 3000, and the learning rate was 0.005. Also, the learning rate of RNNs was changed automatically by applying the algorithm Adam [8]. The parameters of SVM were C=1 and γ=10.

TABLE IV shows the average results of five fold in Experiment II. In Experiment II, we evaluated using input-output data of a participant who excluded in learning data to discuss generality. As the results, in case of learning data A, B, D, E and evaluation data C, accuracy rate and recall rate were 70 % units as low discrimination performance. However, others were 84.3 % at least. The classifiers constructed using non-user's myoelectric signals, achieved high discrimination performance. According to this result, it is considered that non-user's myoelectric signals enable constructed classifiers to have generality to a certain extent. Additionally, it is assumed that the differences between participant C's generating factors of the myoelectric signals and others' ones such as muscle strength, caused low discrimination performance. Because of this, to construct classifier having high generality needs input-output data from a lot of participants.

TABLE IV
THE RESULTS OF EXPERIMENT II

Acuracy rate[%]

Learning Data	B-E	A,C-E	A,B,D,E	A-C,E	A-D
Evaluation Data	A	B	C	D	E
FFNNs	93.7	89.0	78.0	84.7	89.0
RNNs	88.0	88.0	70.0	87.0	92.0
SVM	89.7	85.7	79.0	84.3	88.0

Precision rate[%]

Learning Data	B-E	A,C-E	A,B,D,E	A-C,E	A-D
Evaluation Data	A	B	C	D	E
FFNNs	94.0	90.0	88.0	89.0	89.0
RNNs	90.0	89.0	86.0	87.0	92.0
SVM	91.0	86.0	87.0	89.0	89.0

Recall rate[%]

Learning Data	B-E	A,C-E	A,B,D,E	A-C,E	A-D
Evaluation Data	A	B	C	D	E
FFNNs	94.0	89.0	78.0	85.0	89.0
RNNs	88.0	88.0	70.0	87.0	92.0
SVM	90.0	86.0	79.0	84.0	88.0

D. Experiment III

Experiment III was performed to discuss the method that the constructed classifier relearns by using the myoelectric prosthetic hand user's data after constructing using non-myoelectric prosthetic hand user's data.

As the experiment procedure, firstly, we constructed the classifier of FFNNs and RNNs using 1200 input-output data that consisted of four out of five participants' input-output data. Secondly, we made five data sets which each data set had 60 input-output data, using remaining one participant's 300 input-output data. Thirdly, the classifier relearned using four data sets. Lastly, we evaluated constructed classifier using remaining one data set. In other words, the classifiers were constructed by using a specific participant after prior learning. 5-fold-validation was applied as evaluation method. Figure 8 shows the method of making a data set from a participant. The epochs in prior learning and relearning were 3000, and the learning rate was 0.005. Also, the learning rate of RNNs was changed automatically by applying the algorithm Adam [8]. In the experiment with prior learning, we only performed experiment concerning FFNNs and RNNs so that SVM is not able to relearn. The parameters of SVM were C=100 and γ=100. TABLE V shows the average results of five fold in this experiment with prior learning.

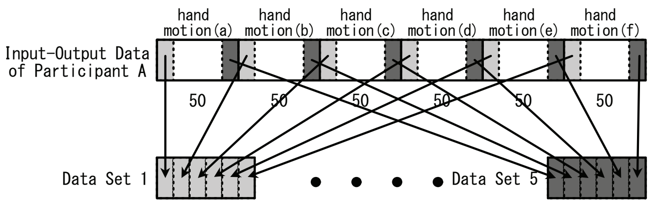

Fig. 8. The method of making a data set from participant A

Also, we constructed classifier without prior learning by using only each participant to compare with the discrimination performance of the experiment with prior learning. TABLE VI shows the results that constructed the classifiers were evaluated by 5-fold-validation. The epoch was 3000 in the experiment without prior learning.

In addition to discussion concerning generality performed in Experiment II, Experiment III was performed to discuss utility of relearning for the myoelectric prosthetic hand user.

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TABLE V
THE RESULTS OF EXPERIMENT III WITH PRIOR LEARNING

Accuracy rate[%]

Prior Learning Data	B-E	A,C-E	A,B,D,E	A-C,E	A-D
Additional Learning and Evaluation Data	A	B	C	D	E
FFNNs	100	92.3	93.3	93.3	89.7
RNNs	98.3	95.0	95.7	94.7	96.7

Precision rate[%]

Prior Learning Data	B-E	A,C-E	A,B,D,E	A-C,E	A-D
Additional Learning and Evaluation Data	A	B	C	D	E
FFNNs	100	91.8	92.6	93.6	89.6
RNNs	98.2	95.8	95.6	94.6	97.8

Recall rate[%]

Prior Learning Data	B-E	A,C-E	A,B,D,E	A-C,E	A-D
Additional Learning and Evaluation Data	A	B	C	D	E
FFNNs	100	91.0	92.4	93.2	89.6
RNNs	98.2	95.0	95.6	94.6	96.6

TABLE VI
THE RESULTS OF EXPERIMENT III WITHOUT PRIOR LEARNING

Accuracy rate[%]

Additional Learning and Evaluation Data	A	B	C	D	E
FFNNs	100	92.0	93.0	92.0	90.0
RNNs	96.0	91.0	91.3	90.0	93.0
SVM	97.0	84.7	85.3	91.7	87.7

Precision rate[%]

Additional Learning and Evaluation Data	A	B	C	D	E
FFNNs	100	92.4	93.6	92.4	90.0
RNNs	96.8	91.6	92.6	90.2	94.2
SVM	98.0	85.8	86.2	92.8	88.4

Recall rate[%]

Additional Learning and Evaluation Data	A	B	C	D	E
FFNNs	100	92.0	93.0	92.0	89.8
RNNs	96.4	91.2	91.2	90.0	93.2
SVM	97.0	84.6	85.2	91.6	87.6

As the results, the classifier constructed by RNNs achieved the highest discrimination performance. In the experiment without prior learning, we constructed classifiers by using a participant's input-output data assuming that the classifier is constructed using the myoelectric prosthetic hand user's data. According to TABLE V and TABLE VI, it became apparent that the classifier with relearning using the myoelectric prosthetic hand user's input-output data achieves better discrimination performance after constructing with prior learning. These results indicate that it is possible to construct the classifier having higher discernment using multi participants' data than a case of only a participant's data. As the reason, in case of using only a participant's myoelectric signals, there is unbalance of input-output data for learning. So, it is considered that FFNNs, RNNs and SVM were unable to acquire suitable discernment for input patterns which are not used as learning data. For that reason, it is considered that learning by using multi participants' input-output data enables unbalance to be compensated. The results of Experiment III proved that the classifier with relearning enables user's burden to decrease as this study's goal. However, there were merely five participants in this experiment. In the future study, we must perform an additional experiment under an increasing number of participants in order to discuss this experiment more deeply.

V. CONCLUSION

This study was performed to reduce the myoelectric prosthetic hand user's burden in constructing classifier which controls the myoelectric prosthetic hand. This paper discussed construction concerning the classifier which has generality. We constructed classifiers of FFNNs, RNNs and SVM by using the myoelectric signals obtained from five participants. And then, we demonstrated some experiments to classify the myoelectric signals. As the results of experiments, RNNs had the advantage for classification in point of accuracy rate, precision rate and recall rate. Above all, in Experiment III, we constructed classifiers by using not only a specific participant's input-output data, but also multi participants' input-output data. So, we considered that the classifier has high discernment if classifier relearns with a specific participant's data after constructing with multi participants' data. As the future study, the experiment for classification will be performed by using more participants' input-output data to discuss more deeply.

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