Japanese Janken Recognition by Support Vector Machine Based on Electromyogram of Wrist

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ABSTRACT

We propose a method which can discriminate hand motions in this paper. We measure an electromyogram (EMG) of wrist by using 8 dry type sensors. We focus on four motions, such as "Rock-Scissors-Paper" and "Neutral". "Neutral" is a state that does not do anything. In the proposed method, we apply fast Fourier transformation (FFT) to measured EMG data, and then remove a hum noise. Next, we combine values of sensors based on a Gaussian function. In this Gaussian function, variance and mean are 0.2 and 0, respectively. We then apply normalization by linear transformation to the values. Subsequently, we resize the values into the range from -1 to 1. Finally, a support vector machine (SVM) conducts learning and discrimination to classify them. We conducted experiments with seven subjects. Average of discrimination accuracy was 89.8%. In the previous method, the discrimination accuracy was 77.1%. Therefore, the proposed method is better in accuracy than the previous method. In future work, we will conduct an experiment which discriminates Japanese Janken of a subject who is not learned.

Keywords: Wrist EMG, SVM, Janken Recognition

1. INTRODUCTION

Recent years, biosignals are receiving attention as a tool of human interface. For instance, there are electroencephalography, pulse wave, and electromyogram (EMG) as an example of the biosignals. Among them, EMG has already applied to many researches [1]-[10], including estimation of arm motion [1] and reflex responses [2], and application to human interface [3][4]. Furthermore, EMG signals were used for manipulator control [5], arm motion analysis [6][7], control of power assisted equipment HAL [8], wheelchair [9], and robot arm [10]. EMG sensors were then attached to arm, shoulder, and lower limbs to measure EMG in many cases because there are many relative muscles and relatively good EMG signals can be measured [1]-[10]. However, it is inconvenient to attach sensors at arm, shoulder, and lower limb in daily living life because we wear clothes. In addition, wet type sensors are often used to measure better EMG. If wet type sensors are dried, those need to be changed to new ones. Therefore, the wet type sensors take a high cost. From these situations, EMG technology is not prevalent in our daily life. On the other hand, there have been several researches using wrist EMG signals, including related work by our group [11]-[15]. In these references, recognition of 7 wrist motions [11][12][14] and Japanese Janken [13], and control of a three hands machine [15] were carried out using wrist EMG signals. From these backgrounds, in this paper we measure EMG by attaching dry type sensors to wrist in the same way as the references [11]-[15], and then discriminate Japanese Janken by wrist EMG data. Our final purpose is the detailed discrimination of hand motions by using wrist EMG. An interface device of wristwatch type is the most suitable for practical use. If we can develop this, we can obtain new interfaces, such as an EMG bracelet. For instance, we can operate AR objects by the EMG bracelet. For this purpose, we discriminate Japanese Janken on offline as the first step in this paper. Motions of Japanese Janken are "Rock-Scissors-Paper" and "Neutral". These motions are shown in Fig.1. "Neutral" is a state that does not do anything.

2. RELATED WORK

There has been much other work related to arm and hand motion recognition by EMG. Many of those used an arm EMG [1]-[7]. The arm has many muscles which can measure better EMG than wrist. Therefore, results of these traditional researches showed a high accuracy in many cases. For instance, classification accuracy of the reference [6] is 91.7%. However, measuring the arm EMG is inconvenient if we wear clothes. From the above, we focus on a method of using wrist EMG. Then, we compare our approach in this paper with the previous method ("Recognition of Finger Motion by Wrist EMG" [13]). The previous method [13] was divided into 5 sections such as an input, a signal processing, a feature extraction, a creating template, and a discrimination sections (Fig.2). The previous method is based on template matching

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Fig.1: *Motions of Japanese Janken.*

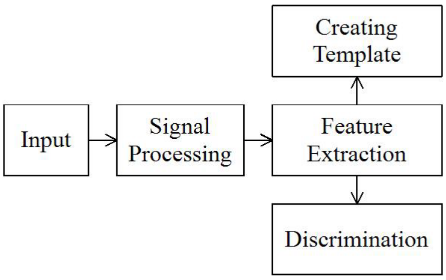

Fig.2: *Flow of the Previous Method [13].*

for speeding up in learning and recognition. However, it caused a long creation time of templates, and as a result, it was a drawback. Besides those, wrist motion recognition using wrist EMG was carried out using statistical methods, neural networks, etc. [11]-[14]. Such a work, however, caused a long training time or relatively low accuracy, and was not adequate for an on-line learning system.

In the following, our previous method is briefly explained. For further details, please refer to [13].

2.1 Previous method [13]

The input section of the previous method measured EMG by 4 channels of dry type sensors. It used Personal EMG (Fig.3) and 3-electrode type sensor (Fig.4) for measuring EMG [16]. The middle of 3 electrodes is a reference (earth electrode) in Fig.4. Position of sensors is shown in Fig.5. Channels 1 and 2 were attached to palm side. Channels 3 and 4 were attached to back of the hand side. Notice that their positions can change every time they are attached. Sampling rate of measuring EMG was 3 kHz, which cannot be changed.

In the signal processing section, fast Fourier transformation (FFT) was applied to the measured EMG data. Parameters of FFT are shown in Table 1.

In the feature extraction section, the previous method applied Principal Component Analysis (PCA) to FFT spectra. However, normal PCA takes an enormous calculation by matrix calculation. Therefore, the previous method used Simple-PCA which did not use matrix calculation [17].

In the creating template section, it created templates before motion discrimination. The template was mean vector of 10 data of each motion.

In the discrimination section, the previous method used the nearest neighbor algorithm.

Experiments of the previous method had been carried out for 3 subjects. Discrimination accuracy of these experiments is shown in Table 2. From this result, the previous method could hardly discriminate the motion of Scissors. This cause is probably that Scissors values were similar to Rock ones which were obtained by PCA.

In the previous method, template matching method was used for discrimination without learning. Therefore, it repeated EMG measurement, until it obtained better templates before discrimination. Therefore, creating the templates took a long time. If we use the previous method to online process, users must wait a long time for setup. It took about 37 seconds. It is necessary and important for users to use EMG recognition systems without waiting. This situation of the previous system is therefore inconvenient and impractical in actual use. Furthermore, as each sensor was relatively far from the others, the sensor positions are likely to change for each measurement.

Fig.3: *Personal EMG [14].*

Fig.4: *Sensor used for EMG measurement [14].*

Fig.5: *Sensor Position of the Previous Method.*

3. PROPOSED METHOD

The previous method had some drawbacks mentioned above. Therefore, we propose a new method. The proposed method is divided into 5 sections such

Table 1: *Parameters of FFT.*

Name	Parameter
Frame length	1,024
Window function	Hamming window

Table 2: *Equivalent inductance and resistance.*

Motion	Subject A	Subject B	Subject C
Neutral	100.0%	98.0%	80.0%
Rock	92.0%	80.0%	90.0%
Scissors	64.0%	2.0%	4.0%
Paper	92.0%	96.0%	100.0%
All	87.0%	69.0%	68.5%

as an input, a signal processing, a feature extraction, a learning, and a discrimination sections (Fig.6). In addition, we use Support Vector Machine (SVM) [18][19]. In the proposed system, by training SVM beforehand, there is no time to wait for use, and discrimination results are obtained at the same time as measurement. The training time of SVM is about 2 seconds. Accuracy obtained by SVM was better than that by a 3-layered neural network in wrist EMG recognition [14].

3.1 Input

The input section of the proposed method measures EMG by 8 channels of dry type sensors. We use P-EMG plus (Fig.7) for measuring EMG [20]. We attach sensors around a wrist as Fig.8 shows. Sampling rate in measuring EMG was 1 kHz. The previous method used 4 channels. However, it could not discriminate the motion of Scissors with high accuracy.

In the wrist part, there are many muscles (tendons). In order to obtain much information from wrist EMG, we must measure more EMG signals corresponding to more muscles. It is thought that 4 sensors in the previous study [13] were insuf?cient. The positions of 4 sensors can

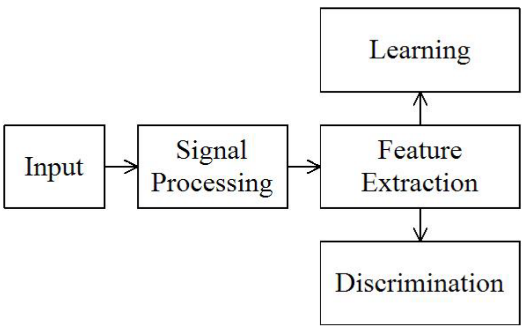

Fig.6: *Flow of the Proposed Method.*

change every time sensors are attached. Therefore, we increase the number of sensors to measure EMG more

Fig.7: *P-EMG plus.*

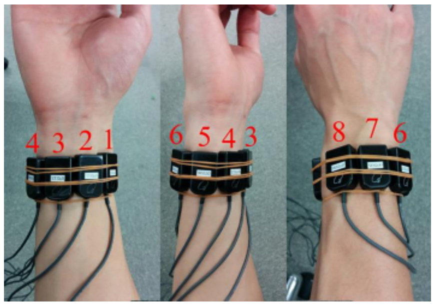

Fig.8: *Sensor Position of the Proposed Method.*

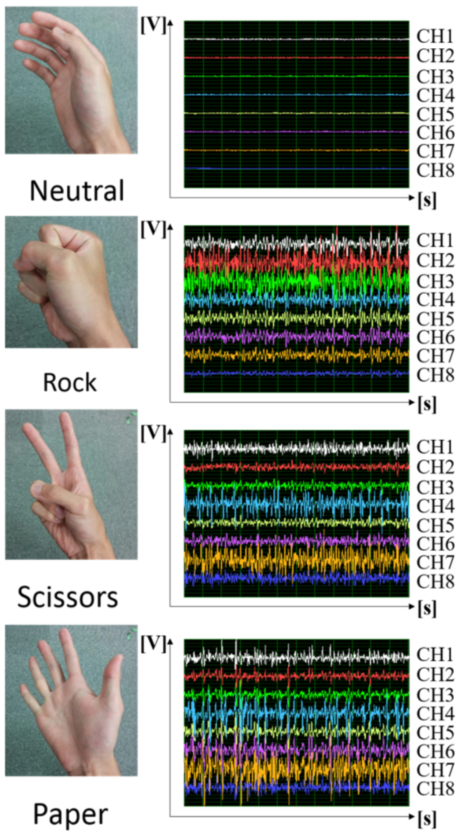

Fig.9: *EMG Data Obtained Using 8 Channels.*

precisely. We attach 8 sensors just around the circumference of wrist as shown in Fig.8. It is thought that position shift can be reduced by this method. Samples of EMG data obtained using 8 sensors are shown in Fig.9.

3.2 Signal Processing

The signal processing section of the proposed method is the same as that of the previous method [13]. Therefore, parameters of FFT are the same as [13] as shown in Table 1. However, the FFT spectra of the proposed method are different from those of the previous method. The sampling rate of the previous method and the proposed method is 3 kHz and 1 kHz, respectively.

3.3 Feature Extraction

The Feature extraction section of the proposed method has several processing steps, such as removing a hum noise, combination, normalization, and rescaling (Fig.10).

3.3.1 Removing Hum Noise

Measured EMG data include the hum noise which is caused by AC power source. In Western Japan, frequency of AC power is 60 Hz. Therefore, we change a value of about 60 Hz of FFT spectra to 0.

3.3.2 Combination

After removing the hum noise, we combine values of channels using a Gaussian function (1).

$$G(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{-\frac{(x-\mu)^2}{2\sigma^2}\right\} \tag{1}$$

In the combination process, we select the values of 0.2 and 0 to variance (σ^2) and mean (μ) in the Gaussian function, respectively. Equation of calculating the combination is given as:

$$C_m = \sum_{i=-4}^{4} G(i) \times X_{m+i} \tag{2}$$

where parameters "X" and "m" show an array of input data and a target channel, respectively (Fig.11). If $m+i$ is less than 0, we add 8 to it. In addition, if $m+i$ is greater than 7, we subtract 8 from it. After this calculation, each channel contains a few values of adjacent channels. After detaching sensors, it is difficult to attach sensors to the same position exactly. Therefore, the proposed method is robust to more or less shift of sensors position by using this approach.

We tested another combination method like moving average. As a result, the combination using the Gaussian function gave better accuracy.

3.3.3 Normalization

After combination, we normalize combined values by linear transformation (Fig.12). By this processing, mean and variance of combined values are normalized as 0 and 1, respectively. Power of FFT spectra depends on muscle strength. Therefore, there is a possibility where the power of FFT spectra varies significantly. However, normalization by linear transformation can suppress the in?uence of variation of FFT spectra.

3.3.4 Rescaling

In this process, at first, we connect all data (Fig.13). We then normalize values into the range from -1 to 1. When there are some variables with different value ranges, even if all variance values are the same, the variable with the biggest variation has a great influence. Therefore, rescaling can prevent this bias in discrimination.

3.4 Learning

In the learning section, parameters of SVM are shown in Table 3. After feature extraction, we obtain 8 FFT spectra, each of which has 512 data by symmetry of FFT spectra. Therefore, SVM learns total 4,096 dimensions in 1 motion. In general, discrimination accuracy of a Gaussian kernel is high compared to another kernel function. However, if dimension of learning data is large, a linear kernel is comparatively better than the nonlinear Gaussian kernel, and can obtain the lowest cost [21]. Therefore, we selected the linear kernel to SVM.

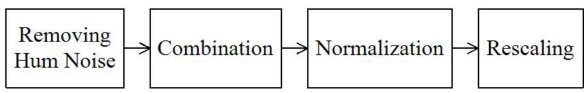

Fig.10: *Flow of the Feature Extraction Section.*

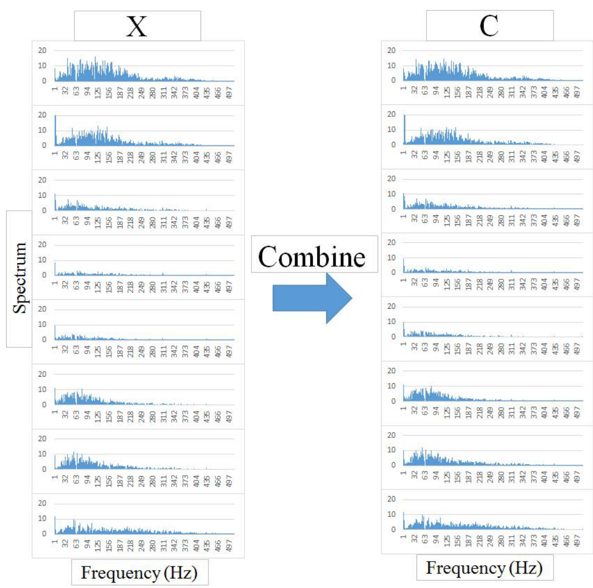

Fig.11: *Combination by Gaussian function.*

Generally, normal SVM cannot classify multiclass problems because SVM is a 2-class discriminator. Therefore, SVM employs a one-to-one classification method for multiclass classification. At first, the one-to-one classification method calculates margin maximization hyperplane between two classes. Then, this method combines all hyperplanes. Therefore, discrimination accuracy of SVM for unlearned data is high because of margin maximization.

3.5 Discrimination

In the discrimination section, the proposed method discriminates Japanese Janken by SVM. Data to be discriminated also have 4,096 dimensions.

4. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, first preliminary experiment is carried out. Next combination process is added to the proposed method to improve accuracy. After experiments, results and consideration are described.

4.1 Preliminary Experiment

We conducted a preliminary experiment for verification whether SVM is valid or not. Therefore, a motion discrimination method of this experiment is different from that of the proposed method. In particular, this method removes the combination process in the feature extraction section to examine discrimination accuracy by using values of just each channel.

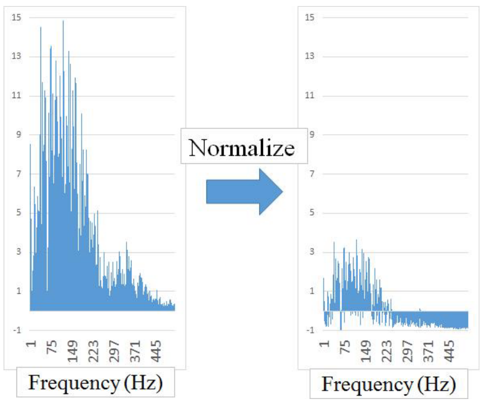

Fig.12: *Normalization by linear transformation.*

Table 3: *Parameters of SVM.*

Name	Parameter
Kernel function	Linear kernel
Number of classes	4
Number of dimensions	4,096
Multi class classification	One-to-one classification

4.1.1 Experimental Conditions

A subject is a male of twenties. The preliminary experiment had 12 pattern conditions. We proposed the method which uses 8 channel sensors in this paper. However, the previous method used 4 channel sensors. Therefore, we examine a difference between 4 channels and 8 channels.

On the one hand, there is a possibility where some information of EMG can be removed when we remove the hum noise from the result of FFT. We therefore evaluate an in?uence of removing the hum noise in each pattern of both 4 and 8 channels. Finally, we consider discrimination accuracy by another normalization method.

4.1.2 Sensor Position of 4 Channels

Figure 14 shows position of 4 channel sensors. We attached each sensor near a muscle (tendon) which moves fingers. The channel 1 sensor was attached near the flexor hallucis longus muscle which bends a thumb. The channel 2 sensor was attached near the flexor digitorum superficialis muscle which bends fingers except for the thumb. The channel 3 sensor was attached near the extensor digitorum muscle which extends fingers except for the thumb. The channel 4 sensor was attached near the

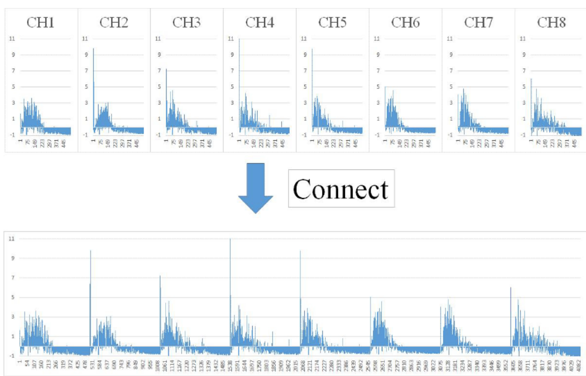

Fig.13: *Connecting all data.*

Fig.14: *Position of 4 Channel Sensors.*

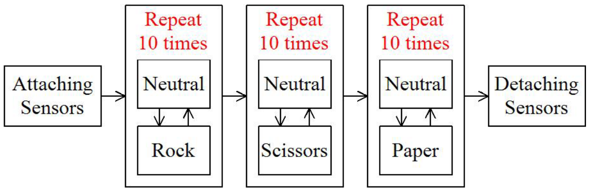

Fig.15: *1 Trial Flow of Experiment to Measure EMG Data.*

long extensor muscle of the thumb. In these sensor positions, the positions of the channels 3 and 4 were slightly out of position in Fig.4. This situation can occur at all measurements. Furthermore, it is difficult to measure all relevant muscle potentials by using just 4 sensors. Therefore there was a possibility where we could not obtain good EMG data for Janken recognition in 4 sensors case. As a result, this can cause low discrimination accuracy especially for Scissors.

4.1.3 Experimental Flow

Figure 15 shows 1 trial flow of experiment to measure EMG data. We conducted this trial 4 times. We carried out attachment and detachment of sensors in each trial. The one trial of measurement took about 15 minutes in total. It is done to evaluate an influence by a shift of sensors positions. Therefore, we conducted each trial at a different day. The number of learning data is 40, which consist of 4 kinds of motion data. Each motion has 5 data in the first and second trials (Fig.16). On the one hand, the number of test data is 64. Each motion has 8 data in the third and fourth trials (Fig.17).

4.1.4 Experimental Results and Consideration

We conducted a preliminary experiment using these conditions, and results of this experiment are shown in Table 4. Discrimination accuracy of the proposed method was 98.4%. Therefore, the proposed method is the best of 12 pattern conditions in Table 4. In Table 4, “Normalization by Total Summation” means results obtained by using normalization based on division by a total value. In addition, the discrimination accuracy of the scissors motion by the previous method was not very good as shown in Table 2. The average discrimination accuracy obtained by the previous method was 77.1%. On the one hand, the discrimination accuracy of the proposed method is drastically improved compared to that of the previous method.

It is thought that there are 2 reasons why the proposed method obtained better result. The ?rst one is the number of channels. The number of channels of the previous method and the proposed method are 4 and 8, respectively. The second one is due to a discrimination method. As a test, we used SVM for data in 4 channels measuring. The discrimination accuracy was then 92.2% by using SVM as shown in Table 4. This result is better than the discrimination accuracy of the previous method. Therefore, SVM is more suitable for EMG discrimination than the nearest neighbor algorithm.

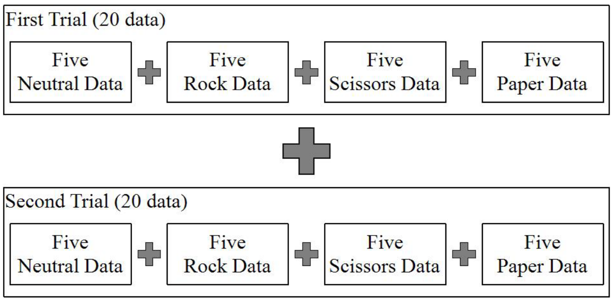

Fig.16: *Training Dataset of the Preliminary Experiment.*

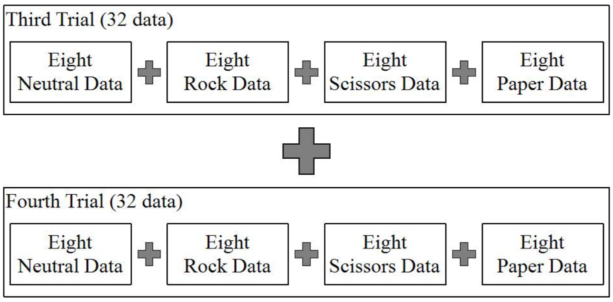

Fig.17: *Test Dataset of the Preliminary Experiment.*

4.2 Experiment

The discrimination accuracy of the preliminary experiment was better than that of the previous method. In addition, learning speed of SVM was fast. Therefore, the proposed method is better than the previous method in accuracy and learning speed. However, the method of the preliminary experiment did not include the combination process in the feature extraction section. We verify whether the combination is valid or not in the following.

4.2.1 Experimental Conditions

We attach sensors around a wrist (Fig.8). Subjects of this experiment are 7 males of twenties. However, SVM learns only separation of a target subject from the others. Therefore, 7 SVMs separately learn corresponding data.

On the one hand, we change conditions and parameters of the combination section as shown in Table 5. We combine values of the channels by using functions. In the combination, we tested two functions. The first one is to calculate average of adjacent channels (channels 1 and 2, channels 2 and 3, ..., channels 8 and

Table 4: *System parameters.*

Number of Channels	Remove Hum Noise	Normalization	Discrimination Accuracy
4 Channels	Not Apply	Nothing	64.1%
		Linear Transformation	85.9%
		Normalization by Total Summation	92.2%
	Apply	Nothing	64.1%
		Linear Transformation	85.9%
		Normalization by Total Summation	92.2%
8 Channels	Not Apply	Nothing	64.5%
		Linear Transformation	84.4%
		Normalization by Total Summation	53.6%
	Apply	Nothing	90.6%
		Linear Transformation	**98.4%** (The proposed method)
		Normalization by Total Summation	85.9%

1), which is a kind of moving average. The other is the use of the Gaussian function to do it. Then, we tested using varying value of variance of the Gaussian function, such as 0.2, 0.5, 1.0, and 5.0.

4.2.2 Experimental Flow

The experimental flow to measure EMG data is the same as that of the preliminary experiment. Therefore, 1 trial ?ow is shown in Fig.15. We conducted this trial 4 times and increased the number of learning data and test data.

The number of learning data is 80, which consist of 4 kinds of motion data. Each motion has 10 data in the first and second trials (Fig.18). The number of test data is also 80. Therefore each motion has 10 data in the third and fourth trials (Fig.19).

4.3 Results and Consideration

4.3.1 Results

Learning time of SVM took about 2 seconds. Table 6 shows discrimination accuracy of experiments using the averaging and the Gaussian functions in the combination process. In Table 6, A, B,..., G show subjects. From this table, average discrimination accuracy of the proposed method for seven subjects was 89.8% in the case of variance=0.2. Table 7 shows detailed results of discrimination by the proposed method.

From the results, discrimination accuracy obtained using the Gaussian function is better than that of the averaging function. It is thought that this result was caused by a difference of the combination method. The averaging function used only one side of adjacent channels. On the contrary, the Gaussian function used both of adjacent channels. For instance, in the averaging function, if the first channel moves to the second channel side, eighth channel will measure EMG similar to that of the first channel. In this case, the average function cannot modify a shift of the sensor position because the average function uses only channels 1 and 2. However, the Gaussian function can modify this case. Therefore, the Gaussian function is robust to a shift of sensor position because this function combines both adjacent channels.

Table 5: *Parameters of FFT.*

Function	Variance
Averaging	
Gaussian	0.2
	0.5
	1.0
	5.0

4.3.2 Consideration

On the other hand, parameters 0.5, 1.0 and 5.0 of the variance were not very good because these include other channels too wide. If many channels are used and integrated, each channel data can have similar values to adjacent channels. Therefore, these variance parameters could not discriminate hand motions clearly. From these results, the variance value of 0.2 would be suited to Janken recognition.

In Table 7, the discrimination accuracy of the scissors motion is not very good in the subjects C and D. In the next step, we therefore try to use a deep architecture of neural networks (deep learning).

5. CONCLUSIONS

In this paper, we proposed a method which can discriminate hand motions. In particular, we measured electromyogram (EMG) of wrist by using 8 dry type sensors. We focused on four motions, such as “Rock-Scissors-Paper” and “Neutral”. “Neutral” is a state that does not do anything. In the proposed method, we applied fast Fourier transformation (FFT) to measured EMG data, and then removed the hum noise. Next, we combined values of sensors based on a Gaussian function. In this Gaussian function, the values of variance and mean are 0.2 and 0, respectively. We then applied normalization by linear transformation to the values. Subsequently, we resized the values into the range from -1 to 1. Finally, a support vector machine (SVM) was used for learning and discrimination. We conducted experiments with seven sub-

Table 6: *System parameters.*

Function	Variance	A	B	C	D	E	F	G	All
Averaging		92.5%	96.3%	85.0%	80.0%	85.0%	91.3%	91.3%	88.8%
Gaussian	0.2	91.3%	96.3%	85.0%	82.5%	86.3%	92.5%	95.0%	**89.8%**
	0.5	80.0%	96.3%	83.8%	73.8%	83.8%	91.3%	92.5%	85.9%
	1.0	63.8%	91.3%	82.5%	68.8%	80.0%	85.0%	85.0%	79.5%
	5.0	57.5%	72.5%	76.3%	53.8%	75.0%	75.0%	71.3%	68.8%

Table 7: *Discrimination Accuracy of the Proposed Method.*

Motion	A	B	C	D	E	F	G
Neutral	100.0%	100.0%	100.0%	90.0%	100.0%	100.0%	85.0%
Rock	100.0%	100.0%	95.0%	100.0%	85.0%	100.0%	100.0%
Scissors	70.0%	85.0%	50.0%	40.0%	95.0%	70.0%	95.0%
Paper	95.0%	100.0%	95.0%	100.0%	65.0%	100.0%	100.0%

jects. Average discrimination accuracy of the proposed method was 89.8%. Therefore, it is shown that the approach using 8 sensors and the Gaussian function is robust to a shift of sensor position because this function combines both adjacent channels. In the previous method, the discrimination accuracy was 77.1%. The proposed method is therefore better in accuracy than the previous method. In future work, we will conduct an experiment which discriminates Japanese Janken of a subject who is not learned, and try to use a deep architecture of neural networks (deep learning).

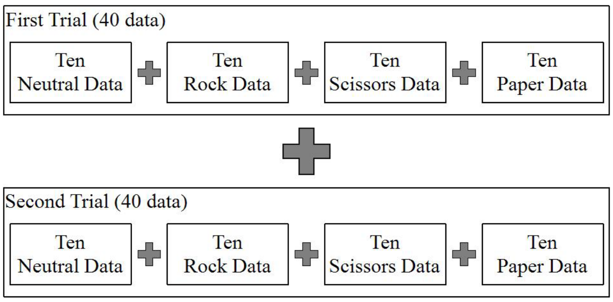

Fig.18: *Training Dataset of the Experiment.*

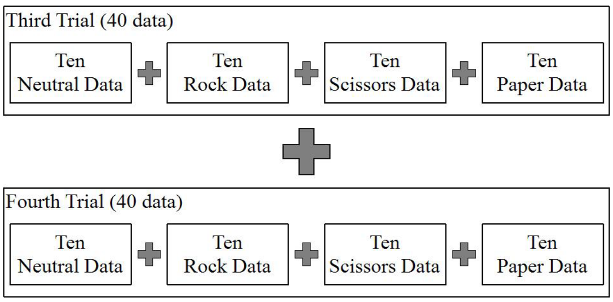

Fig.19: *Test Dataset of the Experiment.*

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