Hand shape recognition using the sEMG of the upper extremity

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Abstract - *In this paper, we propose a hand shape recognition method using the sEMG (surface electromyography) of the upper extremity. The upper extremity sEMG is acquired using Myo which is a wearable device. The target hand shapes are three: Rock, Paper, and Scissors. For hand shape recognition, four features obtained with FFT and wavelet transform are used. SVM and an improved k-NN are used for classifiers. For hand shape recognition, the proposed method performs ensemble learning using these features and the classifiers. The ensemble learning to be used is AdaBoost.M1. As a result of the experiment, the recognition rate of Rock, Paper and Scissors are 86%, 81.3% and 75.6%, respectively.*

Keywords: sEMG, SVM, k-NN, Ensemble learning, Pattern recognition

1 Introduction

Recently, as many see-through HMDs (Head Mounted Displays) have been released, applications using see-through HMDs and AR (Augmented Reality) are to be developed. Such applications allow users to gain an intuitive understanding. For example, in the case of direction guides, the direction instruction and the map are displayed so as to overlap the real landscape in front of the eyes. As a result, the user no longer needs to compare the screen of the smartphone with the real landscape, and can intuitively understand the direction to go. There are Google Glass (Google) [1] and Holo Lens (Microsoft) [2] as famous see-through HMDs. Google Glass is equipped with a microphone, a camera, an IMU (inertial measurement unit) sensor. The operation is done with speech recognition. The operation of Holo Lens is by hand gestures as well as voices. The hand gestures are recognized by the camera mounted in front of Holo Lens. Speech recognition is difficult to use in concert halls where speaking is prohibited and public places where privacy is not protected. Also, the recognition is difficult for the people who are sick or hearing impaired. Gesture recognition with a camera requires a large motion. Therefore, the operation is difficult at crowded places. In view of the above, a see-through HMDs operation method is required rather than speech recognition and gesture recognition by camera.

In this paper, as an operation method of see-through HMDs, we focus on MMI (Muscle - Machine Interface) which is a connection between muscles and machines. We introduce two related studies on MMI. The first one is to steer the wheelchair using the sEMG of arms by Shafivulla Mohammad [3]. The second one is to input letters using the sEMG of faces by Meredith J. Cler [4]. Many studies on MMI are aimed at medical device operations. However, the proposed method is aimed at manipulating AR using MMI. Therefore, it requires several assumptions: used in any environment, easy to wear and remove, and with versatile functionality. In the case of MMI using EMG, electrical signals of human's body are sent to a device. Since it is less susceptible to external environments such as congestion and noise, it can be operated in any environment. The sEMG is non-invasively available so the burden of wearing and removing is taken into consideration.

The sEMG is an action potential transmitted by Volume conduction to be measured on the skin surface. Since the sEMG evaluates the whole muscle fiber activity, it can obtain muscle states sufficiently [5]. Most movements of fingers are influenced by muscles of the upper extremity. By examining muscles state of the upper extremity, it is possible to know indirectly the finger movements. The target hand shapes are three: Rock, Paper and Scissors. These hand shapes include basic hand movements: opening and holding hands. The movements of Rock and Paper are large while the movement of Scissors is small. Therefore, by targeting these hand shapes, the proposed method examines the basic hand movements to compare the large movement with the small movement. There is a related study to recognize hand shape of the rock-paper-scissors[6]. In the study, all the hand shapes are correctly recognized by just images. However, the method requires image sensoring and processing environment while we are interested in using vital data obtained by small and wearable sensors.We introduce two related studies that recognize hand shapes using the sEMG of the upper extremity. The first study by Agamemnon Krasoulis [7] is to use the sEMG and the acceleration obtained from NinaPro [8] database. NinaPro database is open to the public for the purpose of supporting research on advanced hand myoelectric prosthetics to be measured with twelve electrodes. The eight electrodes are equally spaced around the arm while the remaining four electrodes measure the sEMG of a specific muscle. Since specialized knowledge is required to measure sEMG, such a measurement method is very difficult for general users. The

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Fig. 1 Myo


Fig. 2 The placement of Myo

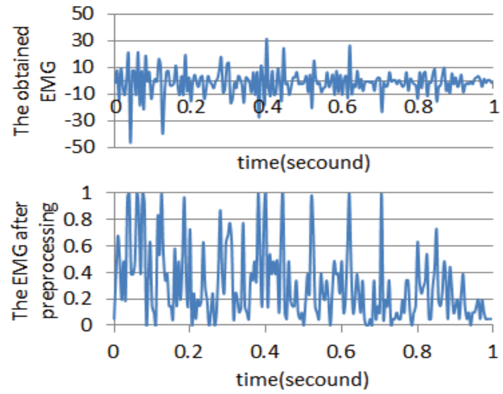

Fig. 3 The obtained EMG and The preproccesed EMG

second study [9] is to use Myo [10] that is used also in this paper. The features used in the study are to compare the sEMG of a resting state with the sEMG of hand shapes to be recognized. Therefore, the method requires measuring the sEMG of resting state beforehand, which is troublesome for general users. Based on the above, in this paper, we propose a hand shape recognition method using Myo that can be worn and removed easily without any expert knowledge. Furthermore, we propose the method to recognize the hand shapes without registering the sEMG in advance. It takes user's physical burden and troublesome into consideration.

The rest of the paper is organized as follows. In section 2, we introduce the processes for the hand shape recognition method and the measuring instrument for acquiring the sEMG. In section 3, the features used for the method are described. In section 4, recognition experiments with the single feature and ensemble learning are performed.

2 The proposed method for hand shape recognition

2.1 Process

The process for hand shape recognition with the sEMG of the upper extremity is shown below.

step-1. Acquire the sEMG of the upper extremity using Myo

step-2. Perform preprocesses

step-3. Calculate four features

step-4. Recognize hand shapes by ensemble learning

In step-1, the sEMG data are obtained for the hand shape recognition among Rock-Paper-Scissors. Myo is used for the data acquisition, which is a wireless armband gesture controller using Bluetooth developed by Thalmic Labs. It is equipped with eight channel sEMG sensors and a nine-axis IMU: a three- axis acceleration sensor, a three-axis magnetic force sensor and a three-axis gyroscope sensor. Fig. 1 shows the channel number for each electrode of Myo. On channel 4 an LED light is located. The channel number is decreased leftward and increased rightward from the channel 4. The sampling frequency is 200 Hz. Since the acquired sEMG data are the amount of EMG activity, there is no unit for the data to be converted in the range of -127 to 127. The wearing position of Myo is the right forearm. Fig. 2 shows the state of wearing Myo. As shown in Fig. 2, the channel 4 is mounted on the extended line of the middle finger on the palm side. In step-2, several preprocesses are performed. The preprocesses include RMS (Root Mean Square), noise reduction and normalization. Since the sEMG consists of electrical activities, the frequency tends to increase as the muscle contracts [9]. The sEMG data focused on the amplitude average is calculated by RMS, which is generally used in EMG analysis. RMS is represented by the following equation. The variable s represents the value of the sEMG at a certain time. The variable T is the time width where RMS is applied.

$$RMS_s = \sqrt{\frac{1}{T}\sum_{i=1}^{T}(s_i)^2} \quad (1)$$

When sEMG is measured, it is expected that noises are mixed due to the displacement conditions of Myo. Noises are removed so that any value does not exceed the average ± 2σ. The normalization is performed in the range of 0 to 1 for the all channels. By performing the normalization, there are no individual differences in the amplitude of the sEMG. Fig. 3 shows the data acquired by Myo and the data performing the preprocesses to. In step-3, features are obtained by calculating FFT (Fast Fourier Transform) and wavelet transformation. The feature obtained by FFT is the order of spectral sums. It represents the relation among the channels. The features obtained by wavelet transformation [11] take account of the time variation of the sEMG. As for the feature extraction methods of step-3 the details are explained in section 3. In step-4, ensemble learning is performed with an SVM (Support Vector Machine) and an improved k-NN (k-Nearest Neighbor algorithm) to recognize hand shapes. By using ensemble learning, the final recognition result is decided by independent classifiers. As a result, since the generalization ability improves, the correct recognition rate also improves. SVM is known as one of best pattern recognition methods. It achieves superior recognition by using a maximum margin. We use SVM as one of classifiers in this paper. The kernel used by the SVM is rbf. An improved method of k-NN is explained in detail in the next subsection. For ensemble learning, AdaBoost.M1 [12] is used. In AdaBoost weights are adjusted sequentially by the result of weak classifiers to improve the recognition results. In this paper, we need to use a multi-valued decision. Therefore, AdaBoost.M1 is used for the boosting.

2.2 An improved method of k-NN

k-NN is known as one of the simplest pattern recognition methods. In k-NN, a majority vote is made by k training data samples with the nearest distance from a given test data sample to decide the class for the test data. In this paper, since k-NN is improved for our purpose, broader classification is obtained. The improved method of k-NN is shown below.

step-a. Calculate parameter k

step-b. Select k training data neighboring from a given test data

step-c. Select k training data neighboring from each selected training data of step-b

step-d. Perform a majority vote by the selected training data

step-e. Decide the class for the given test data class by the majority vote result

In step-a, the optimal k value should be used. In this paper, we obtain it by calculating the gap statistics [13]. In step-b, the closest k training data to a given test data are selected. We use the Euclidean distance for selecting the k samples. In step-c, the closest k training data to each selected training data of step-b are selected. In step-e, the given test data class is decided by the majority vote. In a normal k-NN, a majority vote is performed for the class of selected *k* training data in step-b. When an error value is included in the selected training data, the classifier result is susceptible to the influence. In the case of the improved k-NN, a majority vote is made for the class of selected *k*k* training data in step-c. Therefore, by performing broader classification, the influence of error values can be reduced.

3 Feature extraction method

3.1 Features with FFT

The processes of the frequency component feature are shown below.

step-A. Calculate the spectral sum for each channel

step-B. Rank each channel

step-C. Acquire the orders of channel 3, 7 and 8

In step-A, the total spectral sum for each channel is obtained. The spectrum represents the intensity of each

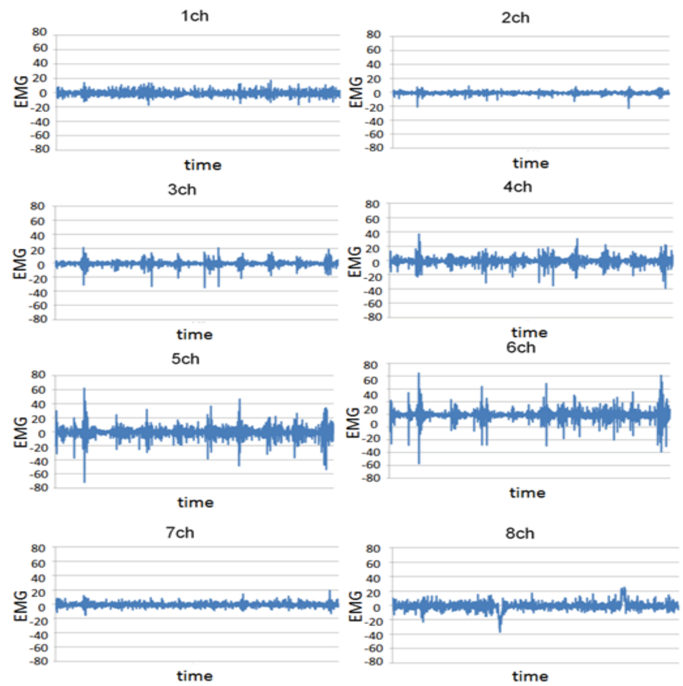

Fig. 4 The EMG when the upper extremity is swung up and down

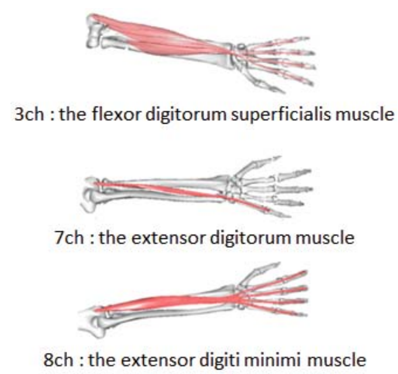

Fig. 5 Muscles corresponding to channels 3, 7, and 8

frequency. By using the spectral sum, the feature focuses just on wave intensity. It is possible to know the amount of muscle activity acquired by each channel. Every time the sEMG is measured, the sum changes. However the relation among the spectral sums of each channel hardly changes. Therefore, in step-B, the total spectral sums are ranked in the descending order. When they are ranked, channel 5 and 6 are excluded. The reason of the exclusion is as follows. When sEMG is measured, there is a possibility that the upper extremity is swung up and down. This motion is not related to the recognition of hand shapes. Since the method focuses just on the intensity of the spectrum, the channel with such sEMG may include considerable noises. Fig. 4 shows the sEMG of each channel when the upper extremity is swung up and down for 7 seconds. From Fig. 4, it is observed that the sEMG of channel 5 and 6 changes greatly. Namely, channel 5 and 6 can be considered to contain sEMG with noises, so they are excluded in step-B. In step-C, the spectral sums are ranked except for channel 5 and 6. The orders of channels 3, 7, and 8

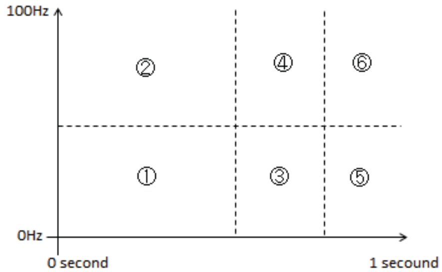

Fig. 6 The area division

are adopted as a three-dimensional feature vector. The channels used for the feature are required to express the hand shapes features in particular. By presuming the muscles that generate the sEMG acquired by each channel, it is judged whether the channels used for the feature are appropriate or not. The muscles correspond to the channel 3, 7, and 8 are shown in Fig. 5. The sEMG mainly acquired by the channel 3 seems to come from the flexor digitorum superficialis muscle [14]. This muscle is divided into two parts: the ulnar head originating from the ulna and the radial head originating from the radius. This muscle relates to flexion of hand joint. Since it is attached to the middle phalanx of the 2-5th fingers, the muscle sEMG is measured especially when the hand is held. The sEMG mainly acquired by the channel 7 seems to come from the extensor digitorum muscle[14]. This muscle relates to extension of the 2-5th fingers. The muscle sEMG is measured especially when the fingers are extended to the hand shapes of Paper or Scissors. The sEMG mainly acquired by channel 8 seems to come from the extensor digiti minimi muscle[14]. The sEMG is acquired especially when the little finger is extended to the hand shape of Paper. Therefore, the channel 3, 7, and 8 are used as a feature obtained with FFT.

3.2 Features with wavelet transformation

The processes of the three features obtained with wavelet transformation are shown below.

step-i. Calculate the spectral value considering time variation

step-ii. Calculate spectral average for each area

step-iii. Combine each area and each channel

In step-i, the time variation of the sEMG is taken into account by calculating the wavelet transform. We use a continuous wavelet transformation. The mother wavelet function is Morlet. The value σ that represents the width in time direction of the window function is 4. The range of the frequency where wavelet transformation is performed is 0 Hz to 100 Hz. In step-ii, in order to focus on the time variation of the spectrum, the wavelet transformed sEMG is divided into six areas for frequency and time. The areas to be divided are shown in Fig. 6. On the time axis, it is divided into three areas: 0 to 0.5, 0.5 to 0.75 and 0.75 to 1 seconds. On the frequency axis, it is divided into two areas: 0 to 50 and 50 to 100 Hz. The spectral average for the each area is calculated. Since the value considering the time variation and the intensity of the frequency is acquired, it is possible to focus on the spectral distribution for each time. In step-iii, the combinations are obtained from the spectral average of each area calculated in step-ii. They represent the hand shape characteristics. For the combinations of the channels and areas, the details are given in subsection 4.2.

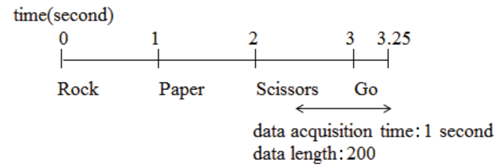

Fig. 7 The call and the data acquisition time

Table 1 The clustering result with k-means

Number of cluster	Rock	Scissors	Paper
1	87	7	13
2	174	54	15
3	8	88	124
4	28	135	81
5	3	16	67

Feature *b*

Number of cluster	Rock	Scissors	Paper
1	65	4	4
2	35	135	84
3	191	57	21
4	2	13	67
5	7	91	124

Feature *c*

Number of cluster	Rock	Scissors	Paper
1	6	85	129
2	193	53	16
3	2	15	61
4	29	131	85
5	70	16	9

4 Experiments

4.1 Data measurement

The subjects are 30 healthy twenties women who are right-handed. The sEMG measurement is performed according to a priming call that consists of five words in Japanese. The call and the data acquisition time are shown in Fig. 7. At the measurement, the subjects are instructed to move only fingers as much as possible. The subjects measure the hand shapes of Rock, Scissors, and Paper each 10 times so they measure 30 times in total. Finally, the 900 sEMG data are obtained.

4.2 Preliminary experiment

In this subsection, the experiments are conducted on the combinations of the features obtained from wavelet transformation described in subsection 3.2. The dimension of the combination is 2 to 4. The combinations are examined in round-robin fashion. The combination is clustered to see if it represents the hand shape features with using k-means clustering. The number of clusters varies within the range of 3 to 6. Let (n, a) represent area a of channel n. Especially, we find three combinations that express the features of each hand shape: a 4-dimensional feature of (4,4), (4,5), (7,4), (8,5), a 3-dimensional feature of (4,5), (7,4), (8,5) and another 3-dimensional feature of (4,4), (7,4), (8,5). In the following, we call the four-dimensional feature of (4,4), (4,5), (7,4), (8,5), the 3-dimensional features of (4,5), (7,4), (8,5) and (4,4), (7,4), (8,5) features a, b, and c, respectively. Table 1 shows the clustering result of the three features. In Tab. 1, when the number of cluster is five, clusters for each hand shape are more clearly formed. In the case of feature a, Rock, Scissors and Paper are clustered dominantly into Cluster 2, 4 and 3, respectively. In the case of feature b, Rock, Scissors and Paper are clustered dominantly into Cluster 3, 2 and 5, respectively. In the case of feature c, Rock, Scissors and Paper are clustered dominantly into Cluster 2, 4 and 1, respectively. Since they are assumed to represent each hand shape feature, the feature a, b and c are used as the features obtained from wavelet transformation.

4.3 Experiment methodology

The results of the preliminary experiments reveal that single feature classifiers seem to be difficult to classify the sEMG sufficiently. To achieve highly general classification, we use an ensemble learning as well as single feature classifiers. Since ensemble learning uses several features and classifiers, highly versatile classification is expected. We use AdaBoost.M1 as ensemble learning. Furthermore, the resultant weight of Adaboost.M1 is to be improved for higher recognition. The following three kinds of experiments are conducted.

Experiment 1. Recognition using single features

Experiment 2. AdaBoost.M1

Experiment 3. AdaBoost.M1 with manually improved weights

In all experiments, the number of training data and test data are 720 (subjects: 24) and 180 (subjects: 6), respectively. Cross validation is performed five times. Subjects are divided in two groups: for training data and test data. Namely, any subject does not exist whose data are used both for training and test. In k-NN, the value k is decided by the gap statistic. In the case of the feature of FFT, a, b and c, k is 5, 11, 9 and 11, respectively. In experiment 1, four features obtained with FFT and wavelet transformation and two classifiers of SVM and improved k-NN are used. Thus we have eight classified results using single features. In experiment 2, AdaBoost.M1 using the eight classifiers of experiment 1 is performed. We get the recognition rate of an ensemble learning that combines four features and two classifiers. In experiment 3, in order to improve the recognition rate of AdaBoost.M1, we increase the weight of the weak classifier with the best recognition rate while the weights of other weak classifier are adjusted so that as many weak classifiers give good affection to the resultant recognition rate as possible affect the classified result. The AdaBoost.M1 in experiment 2 and experiment 3 is terminated when the number of boosting times reaches 20.

Table 2 The recognition result using single features

	SVM			
	Feature *f*	Feature *a*	Feature *b*	Feature *c*
Rock	84.3%	86%	86%	85%
Scissors	75%	70%	69.3%	62.9%
Paper	77%	74%	72.6%	75.3%
average	78.7%	76.6%	75.9%	74.4%

	An improved k-NN			
	Feature *f*	Feature *a*	Feature *b*	Feature *c*
Rock	76.3%	89.3%	89%	88%
Scissors	72.3%	57.6%	62.3%	55.6%
Paper	69%	72.3%	71.6%	73.6%
average	72.5%	73%	74.3%	72.5%

4.4 Results and discussion

In this subsection, the results and discussion of the three experiments described in the previous subsection are described.

4.4.1 Single feature

Table 2 shows the recognition result of hand shapes in experiment 1. In the following, the feature obtained from just FFT is defined as the feature *f*. In SVM using feature *f*, the recognition rate of all hand shapes is 75% or more. The average recognition rate is 78.7% that is the highest recognition rate. Focusing on each classifier, SVM has higher average recognition rates with any features than improved k-NN. Except feature *f*, improved k-NN has higher recognition rate of Rock than SVM. In all recognition results excluding improved k-NN using feature *f*, the hand shape of the highest recognition rate is Rock, the next is Paper and the lowest one is Scissors.

The reason why the average recognition rate of SVM is better than improved k-NN is presumed that improved k-NN performs broader classification. In improved k-NN, when the size and the density of a cluster where a test data may belong are small, the classification employs long-distance training data. Therefore, a majority vote may be performed with training data in wrong clusters. In SVM, since the cluster of a test data is decided by a boundary of clusters, the influence of the cluster size and the density is presumed to be small. The feature *f* tends to be different from other features: the recognition rate of Rock using improved k-NN is higher than SVM or the order of recognition rates is different. The reason is that feature *f* is obtained from calculating FFT so it can represent some special features different from the other features. The reason why the order of recognition rate is Rock, Paper then Scissors is the difference of the muscles that make up each hand shape. The muscles used in the hand shapes of Rock and Paper are different from each other. The hand shape of Scissors uses the both muscles used in Rock and Paper. Therefore, it is inferred that the hand shapes of Rock and Paper are easy to be classified while Scissors is difficult.

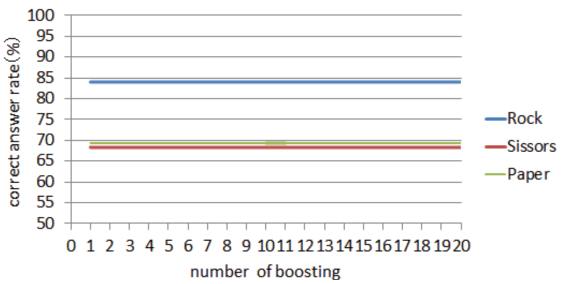

Fig. 8 The recognition rate with AdaBoost.M1

Table 3. The weak classifiers and the weights

Number of boosting	Weak classifier	weight
1	SVM using feature *a*	1.80159
2	SVM using feature *f*	1.058124
3	An improved k-NN using feature *f*	0.09089

4.4.2 Adaboost.M1

The result of experiment 2 is shown in Fig. 8 where the horizontal and the vertical axes represent the number of boosting and the recognition rates of each hand shape, respectively. In experiment 2, there is no change in the recognition rate when the number of boosting is increased. The recognition rates of Rock, Scissors and Paper are 84%, 68.3% and 69.3%, respectively. The average of three hand shapes is 73.8%. The recognition rate is about 5% below the result of SVM using feature *f* with the highest recognition rate in experiment 1. Table 3 shows examples of weak classifiers and the weights obtained by AdaBoost.M1. We observe that boosting is terminated since the error rate exceeds 0.5 when the number of boosting is 4. The weight of SVM using feature a is the largest of about 1.8. The next is SVM using feature *f* and the weight is about 1.0. The last is improved k-NN using feature *f* and the weight is about 0.09. Thus, the weight sum of the 2nd and the 3rd weak classifiers is not greater than the weight of the 1st weak classifier.

The reason why the recognition rate of AdaBoost.M1 does not change is presumed that the result is obtained only by a specific weak classifier as shown in Tab.3. It cannot reflect the results of some weak classifiers. Also, among the five time cross validation, the result of the weak classifiers with the highest recognition rate in experiment 1 is reflected only once. Therefore, it is presumed that the recognition rates of all hand shapes becomes low. From the above, in experiment 3, the weight of SVM using feature *f* that provides the highest recognition rate in experiment 1 should be increased. Furthermore, the weights of each classifier should be improved so that ensemble learning is performed with as many weak classifiers as possible.

4.4.3 Adaboost.M1 with improved weights

In experiment 3, the weights of the weak classifiers with high recognition rates are increased. In addition, weights are improved so that many weak classifiers are used in ensemble learning. The improvement method is shown below.

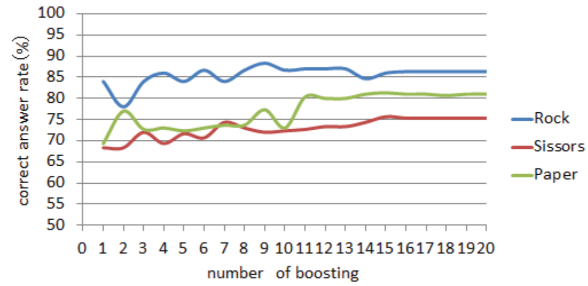

Fig. 9 The recognition rate with an improved AdaBoost.M1

- Double the weight of SVM with feature *f*
- Set the weights of other weak classifiers to 1

Since the weight average of SVM using feature *f* is about 1.2 in experiment 2, the weight is doubled to improve the ensemble learning. The weights of other weak classifiers are set to 1. By doing so, the weak classifier with the highest recognition rate in experiment 1 is more strongly reflected in ensemble learning than in experiment 2. By making the weights of other weak classifiers the same, the ensemble learning is performed with many weak classifiers. The result of the improved AdaBoost.M1 is shown in Fig. 8 where the horizontal and the vertical axes represent the number of boosting and the recognition rates of each hand shape, respectively. As the number of boosting times increases, we observe that the recognition rates of each hand shape become high. When the number of boosting times reaches 15, the recognition rates of each hand shapes is converged. The number of boosting times and the recognition rate with the highest recognition rates of each hand shape are shown below. The recognition rates of Rock, Scissors and Paper are 88.3%, 75.6% and 81.3% with the boosting times of 9, 15 and 15, respectively. When the boosting times is 15, the average recognition rate of three hand shapes is the highest. Finally, we observe that the recognition rates of Rock, Scissors, Paper and the average are 86.0%, 75.6%, 81.3% and 81% when the boosting times is 15.

As the number of boosting times is increased, the recognition rates of each hand shape are improved. It means that the final result is obtained with many weak classifiers. Only the hand shape of Rock records the highest recognition rate when boosting times is 9. Since the recognition rates of the other hand shapes are not so high, the Rock cluster is generated without much influence from other two hand shape clusters. Compared with experiment 1, the recognition rate is about 2.3% higher. By improving the weights of AdaBoost.M1, the recognition rates are improved in any hand shapes. The reason is that many weak classifiers are used while placing emphasis on the weak classifier of SVM using the feature *f*. Therefore, we believe the improvement of AdaBoost.M1 is appropriate. Regarding the number of boosting terminations, as shown in Fig. 9, the recognition rate is converged when the boosting times reaches 15. Therefore, the maximum number of boosting times should be 20 in this experiment.

5 Conclusions

In this paper, we propose a method of hand shapes recognition using the sEMG of the upper extremity. For the recognition of hand shapes, ensemble learning using four features and two classifiers is performed. The four features are extracted from calculating FFT and wavelet transformation. The feature obtained from FFT is focused on the spectral intensity of the sEMG. The features obtained from wavelet transformation are divided into six areas regarding time and frequency in order to take time change of the sEMG into account. They focus on the spectral intensity in each area. The classifiers are SVM and an improved k-NN. By using multiple classifiers, weak classifier candidates for ensemble learning are increased. The target hand shapes are three: Rock, Paper and Scissors. To show the versatility of the proposed method, we have 30 subjects for experiments. In the recognition result of single features, the result of SVM using the feature obtained from FFT is the highest recognition rate of 78.7%. In the result of the improved AdaBoost.M1 as ensemble learning, the recognition rate achieves 81%. The recognition rates are improved compared with single features. From the above results, the method proposed in this paper is effective for the recognition of the three hand shapes: Rock, Paper and Scissors.

For future work, we aim to further improve the recognition rate. In this paper, we focus on only the spectral intensity. Therefore, we calculate the features in consideration of correlation between channels. In the target hand shape, we also analyze the hand shapes that are commonly used on a daily basis such as "picking" and "pointing". As the result, we would like to make it more intuitive operation methods towards a see-through HMD interface.

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