Development of Wrist Contour Measuring Device for an Interface Using Hand Shape Recognition

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Abstract

Recently, gesture recognition is widely used as interface. Popular gestures are mainly arm motion and whole body motion. Although hand shape is a good sign that can express rich information with small motions, few applications are in practical use. That is because the existing methods have several problems; blocks of finger sense and interference with finger motion, restrictions of hand position and posture, and complex initial configurations. In this study, we try to recognize hand shapes by observing the wrist contour, which varies with finger motions. We have developed a robust wrist-watch-type device that captures wrist contour, and have collected data from a substantial number of subjects. With the collected data, we conduct hand shape recognition experiments in several conditions. To overcome the positioning deviations and individual differences, two feature types are designed. Through the experiment, potential of the features is confirmed, and some effective features are picked up. In addition, concerning the design of recognition target properties, we examine the number of target hand shapes and the combination of hand shapes through the experiment, and several clues for target design are revealed.

keywords: hand shape recognition, human machine interface, novel sensor, wearable device, wrist contour

1 INTRODUCTION

There are an increasing number of applications that use gesture recognition as interface. In home use, gesture recognition is getting popular mainly as a controller of TV/Video; Wii(R) by Nintendo captures user's arm motions with accelerometers and a camera integrated in the controller, and Kinect(R) by Microsoft captures user's whole body motions using visual and depth cameras. These devices are specialized in recognition of large body motions, that means they are not good at monitoring small body motions such as hand and finger motions. That is because they have limitations in resolution and accuracy. As we can see in sign languages and hand signals, hand shape is a good sign that can express rich information with small motions. Therefore, realization of hand shape recognition expands the possibility of many applications as natural user interfaces. For example in home use, promising

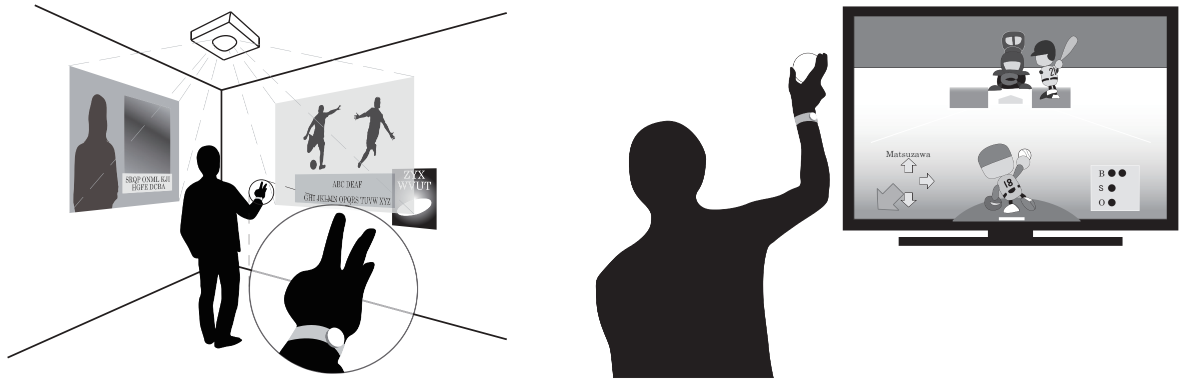


Figure 1: Application examples. Left: Control of multiple displays with an advanced device.
Right: Gaming interface used in a baseball game.

applications with hand shape gestures are control of home electronics including TV and PC, and a gaming interface (e.g. capturing baseball pitching motions) as Figure 1 shows. However, existing methods have several problems to realize these applications.

There are three major hand shape recognition methods[1]. Their features and problems are as follows: **Data glove**[2][3]: A user attaches a glove-type device that has bend sensors at each finger joints. This method realizes high recognition performance because finger joint angles are measured directly. However, it requires much care and attentions to set up in such a way that each bend sensor must be located at the right position. Besides, the device sometimes blocks finger sense or interferes with finger motions. **Camera vision**[4][5][6]: With camera installed at a room or attached to human body, the system recognizes hand shapes with image processing technologies. This method is the most presently popular method for practical use, and it performs well if a camera acquires an image from appropriate direction. However, to recognize hand shape, two restrictions are required; 1. The target hand must be in the range of camera, and occlusions by other body parts should not happen. 2. The target hand should be postured in certain direction required by the system. These restrictions limit position or posture of the user and the hand, and they might be barriers when combining hand shape recognition and other gesture recognitions. **Electromyogram (EMG)**[7][8]: With signals from electrode attached to user's arm, the system detects myoelectric potential and estimates hand motions. The advantage is that there is no disturbance on hand motions and no restrictions of place and posture. However, its initial configuration processes are troublesome; 1. A user needs to clean up the attaching place. 2. It needs to apply a wet electrode or attach a dry electrode with certain pressure. 3. It needs fine positioning of the electrode. 4. Numerous calibration data are required to recognize precise hand shapes.

To summarize the problems mentioned above, existing methods have three problems: blocks of finger sense or interference with finger motions, restrictions of hand position and posture, and complex initial configuration processes. To address these problems, we propose a novel hand shape recognition method

based on "wrist contour" variations with finger movements[9].
Measuring small area; "wrist", a mobile hand shape recognition device with little disturbance on hand motion can be realized. Table 1 shows the comparison of related works, the potential of our approach and our achievements in this paper.

Table 1: Comparison of related works.

Approach	Accuracy	Less disturbance on hand motion	Conciseness of setup processes	Can be used anywhere	Less occupying area on the body	Low cost
Data glove	★★★	★	★★	★★★	★★	★
Camera (Fixed)	★★★	★★★	★★★	★	★★★	★★★
Camera (Wearable)	★★	★★	★★★	★★★	★	★★★
EMG	★	★★★	★	★★★	★★	★★
Our method (potential)	★★	★★★	★★★	★★★	★★★	★★★
Our method (current)	★	★★	★★	★★★	★★★	★★★

★★★: Excellent ★★: Good ★: Fair

The main contributions of this paper are; 1. We developed a robust wrist-watch-type device that captures a wrist contour, and collected data from substantial number of subjects. 2. To overcome positioning deviations or individual differences, two feature types are prepared, and the experiment demonstrates improvement of the hand shape recognition performance. 3. Concerning the design of recognition target properties, we examine two topics, the number of target hand shapes and the combination of hand shapes, through the experiment.
This paper is organized as follows: Section 2 presents the principle of wrist contour variation and our approach. Section 3 presents the details of our developed wrist-watch-type device for wrist contour measurement. Section 4 describes the procedure of data collection and the basic analysis of the collected data. Section 5 discusses the design of feature types and the procedure of hand shape recognition. Section 6 presents the experiment to evaluate the designed feature types. Section 7 presents the experiment to discuss the number of target hand shapes and the combination of them. Section 8 presents the conclusions.

2 PRINCIPLE and CHALLENGES

Principle of wrist contour variation We designate a wrist cross-section contour as a wrist contour. Muscles and tendons for finger movements exist in from fingers to elbows and they are compacted near the elbow. Around the wrist, however, muscles and tendons branch to some extent. To move fingers, muscles and tendons extract/contract or shift around, that makes deformation of the wrist surface (Figure 2). Accordingly, we are trying to recognize hand shapes by observing the wrist contour variation.

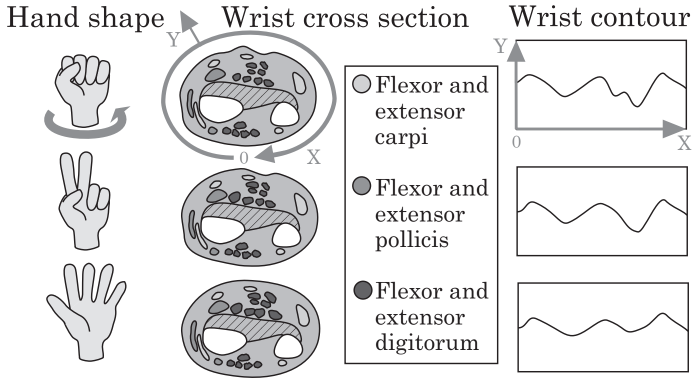


Figure 2: Wrist contour variation principle.

Challenges To realize wrist-contour-based hand shape recognition, we address three challenges.

1. Development of a robust wrist contour measuring device.

We develop a wrist-watch-type device for wrist contour measurement. This device has a flexible band to measure gaps between the band and the surface of the wrist over the whole circumference. Improvement of wearability and reliability is necessary for large scale data collection, therefore, we try to make the device robust.

2. Design of features

The structure of human body makes several problems. First, although muscles and tendons for finger movements branch to some extent around the wrist, they are not completely split but overlapped each other. In addition, around the wrist, there are also muscles and tendons for wrist bending and pronation. They are overlapped with the ones for finger movements. Consequently, it is a hard task to acquire the variation of each muscle or tendon independently. Second, the attaching configuration differs every time in radical, radial and roll direction. Moreover, slippage from the first position may occur when using the device. Third, individual differences of the wrist contour make it difficult to utilize other subjects' data. In order to reduce the configuration processes, it is preferred to utilize other subjects' data acquired previously. That means construction of a robust recognition system is necessary to overcome individual differences. For these reasons, we must design features to overcome overlaps of muscles and tendons, positioning deviations and individual differences.

3. Design of recognition target properties.

Assuming the usage as an interface, we focus on a classification task of hand shape. Although the number of target hand shapes and the combination of hand shapes should be determined according to applications, we need some clues to design those properties. Therefore, we conducted an experiment to examine the relationships between recognition performance and the number of target shapes or the combination of them.

Concerning these three challenges, our work is explained in the following sections. As for challenge 1, the details of the device and data collection are described in section 3 and section 4. As for challenge 2, the design of features and an experiment comparing the features are explained in section 5 and section 6. As for challenge 3, an experiment to search clues to design of recognition target properties is explained in section 7.

3 WRIST CONTOUR MEASURING DEVICE

We developed a wrist-watch-type device to measure wrist contours. In the design of the device, we assumed following human constraints.

- Muscles and tendons for finger movements are approximately 5 mm in diameter.
- Radial variation of wrist contour is approximately 5 mm at maximum.
- Wrist circumference is approximately 150$\sim$170 mm.
- Wide band on the wrist might interfere with human arm motions.

There are individual differences in the size of wrist and the position of tendons. Therefore, the sensor elements are arranged in lines so that the sensor device would be robust to individual diffrences and attaching positions. Consequently, the required specifications of the device are configured as follows.

- Sensor pitch needs to be smaller than 2.5 mm in circumference.
- Radial resolution of the sensor needs to be precise less than 0.1 mm.
- Measurement area needs to be at least 170 mm in circumference.
- The band should be narrower than 30 mm.

In accordance with these specifications, we developed a wrist contour measuring device (Figure 3). This device consists of two parts. One is the measurement part and the other is the battery and control part. The measurement part is a wrist-watch-type part and it is connected to the battery and control part by a wire. Details of each part are as follows.

- **The measurement part**
  This part is for measurement of a wrist contour. It has two bands; the measurement band and the fixing band. On the measurement band, two arrays of 75 photo reflectors are mounted as distance sensors. The band can measure the gaps between the band and wrist contour surface in 2.5 mm pitches. Output value of a photo reflector decreases as distance between the sensor and the target increases. But it is not monotone in the closest area. To avoid the closest area and reduce stress on the user, silicone rubber spacers are attached on the both side of the band.

- **The battery and control part**
  This part includes a control circuit, a wireless module and a battery. It acquires sensor data from the measurement band via a wire, and transmits the data to a monitoring computer wirelessly.

We selected a photo reflector “NJL5901AR-1” (produced by New Japan Radio Co.) considering its size and measurement range. Each photo reflector needs to be calibrated with distance because the output of a photo reflector is non-linear with distance, and photo reflectors have individual differences (Figure 4). We recorded outputs of each photo reflector on a one-axis translation stage while changing the measuring distances from 0 to 10 mm in 0.05 mm pitches . Based on the recorded output-distance conversion map, 0.01 mm radial resolution is achieved in the range of 0∼3.5 mm. As Figure 5 shows, outputs are converted linear to distances.

Here, we will summarize technical artifice to make the device more stable and robust enough for repetitive experiments.

First, we use shift registers for sensor output switching. If all sensor elements are connected directly to the control IC, the width of the measurement band becomes too wide. In addition, numerous electrical lines reduce the band's reliability. By switching sensor outputs of 75 photo reflectors in one array, sensor output lines for one array are unified. Because shift registers can be implemented with small IC chips, the narrow band width of 25 mm can be achieved keeping the flexibility of the band.

Second, we prepare a fixing band to assist the attachment of the measurement band. Wearability is potentially important for a wearable device. By attaching the fixing band before attaching the measurement band, a user can smoothly attach the device and decide the position of the measurement band. In addition, the fixing band reduces slippage from the first position when using the device.

The specifications of the developed device are as follows.

- Measurement pitch is 2.5 mm.
- Radial resolution is 0.1 mm (Range: ∼3.5 mm).
- Measurement area is up to 185 mm.
- Measurement band width is 25 mm.
- Sampling rate is 10 Hz.

4 DATA COLLECTION

4.1 Configuration of data collection

We collected substantial number of wrist contour data with the developed device. 28 subjects (20's ∼ 50's, male and female) participated in this data collection. We prepared 12 hand shapes (Figure 6), and designated them as one set. Wrist contour data were collected six sets for each subject. In this data collection, arm posture was fixed as shown in Figure 7 because wrist contours vary dramatically with wrist pronation. The procedure of data collection was as follows.

Step 1 The measurement part is attached on the wrist in rough alignment.

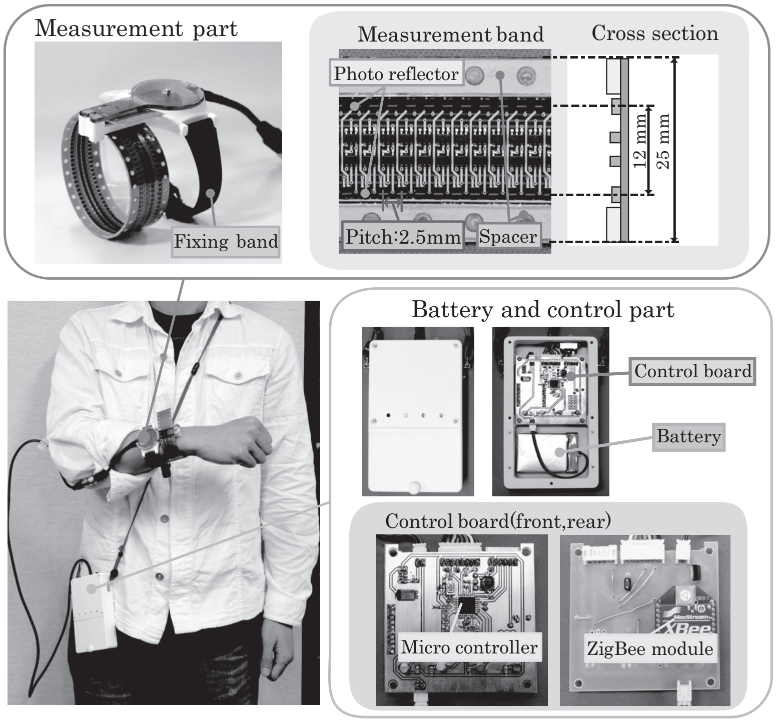


Figure 3: Wrist contour measuring device.

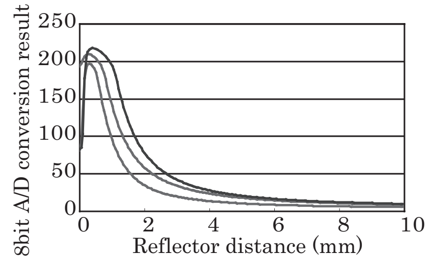


Figure 4: Photo reflector output variation.

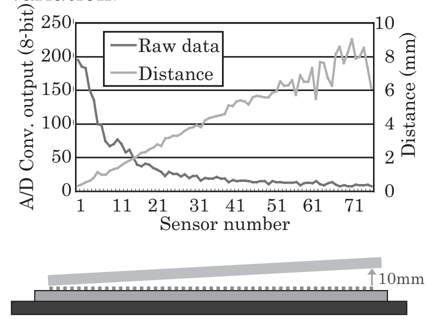


Figure 5: Output conversion example: Measuring a slanted board.

Step 2 A display shows a hand shape illustration to the subject, and the subject imitates the hand shape, and then wrist contour data are recorded.

Step 3 After recording wrist contour data of all hand shapes (one set), the device is taken off.

Step 4 Repeat Step 1∼3 six times for each subject.

Finally, 2,016 wrist contour data were collected; 28 subjects × 6 sets × 12 hand shapes.

4.2 Basic analysis on wrist contour data

Examples of collected wrist contour data are shown in Figure 8. The upper graphs represents the comparison of wrist contour data from one subject. Each line shows wrist contour data of one hand shape. The center graph shows the ones from another subject. Comparing two graphs, we can see that wrist contour data vary considerably with subjects. Comparing data in one graph, it is obvious that wrist contour vary with hand shapes. Surely some combinations (e.g. One finger and Thumb and index) are very similar and supposed to be hard to distinguish. Comparing data of the same hand shapes in two graphs, some common characteristics can be observed. We have to extract features that emphasize such common relationships from wrist contour data. In the lower graphs, the wrist contour data of one hand shape (Two fingers, or Thumb and little) from one subjects are shown. Each data are picked out from different set, that means the difference of the data comes from mainly positioning deviation. It is

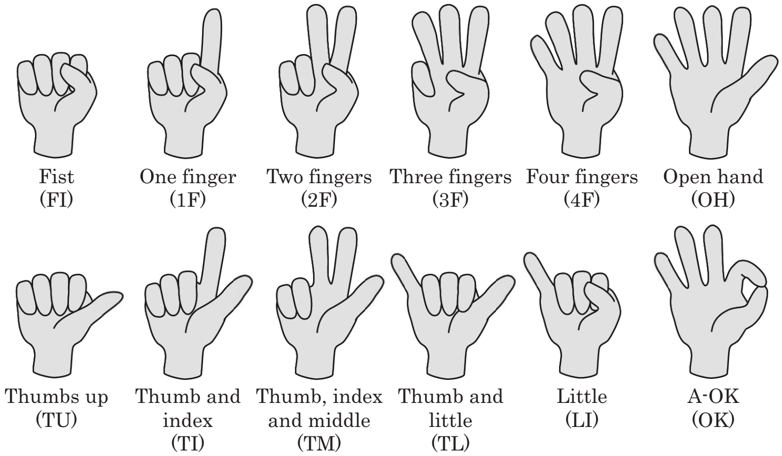


Figure 6: Hand shape 12 classes.

Figure 7: Posture while in data collection.

revealed that wrist contour data vary with positioning even in the same subject and in the same hand shape. Please refer to appendix A for details of the collected wrist contour data.

5 HAND SHAPE CLASSIFICATION

The procedure of the wrist-contour-based hand shape classification is described below.

5.1 Design of features

Wrist contour data differ not only with hand shapes but also with attaching positions and individuals. To overcome these differences, two potential feature design types are prepared.
One feature type is "normalized contour data". Because each muscle and tendon is different in thickness, each sensor element has different variation range of distance. The process samples the maximum and minimum distance for each sensor element, and normalizes distance data into 0 to 1 (Figure 9). With this process, small local variations can be emphasized. On the other hand, the slippage of the band might be great noise.

The other feature type is "contour statistics". They are statistics from wrist contour data (Eq. 1). Statistics are normalized by two hand shapes; Fist and Open hand. 46 statistics are designed and selected as described below. Sum of distances (Eq. 2), Sum of differences (Eq. 3), Number of peaks, Number of valleys, Maximum distance, Minimum distance, Ratio of former half sum and latter half sum (Eq. 4), Maximum monotone increment value (Eq. 5), Maximum monotone decrement value, Maximum monotone increment width, Maximum monotone decrement width, Distance histogram (8 bins), its score comparing with the one of Fist, Neighbor difference histogram (8 bins), its score comparing with the one of Fist, Open hand difference histogram (16 bins), its score comparing with the one of Fist (Eq. 6).

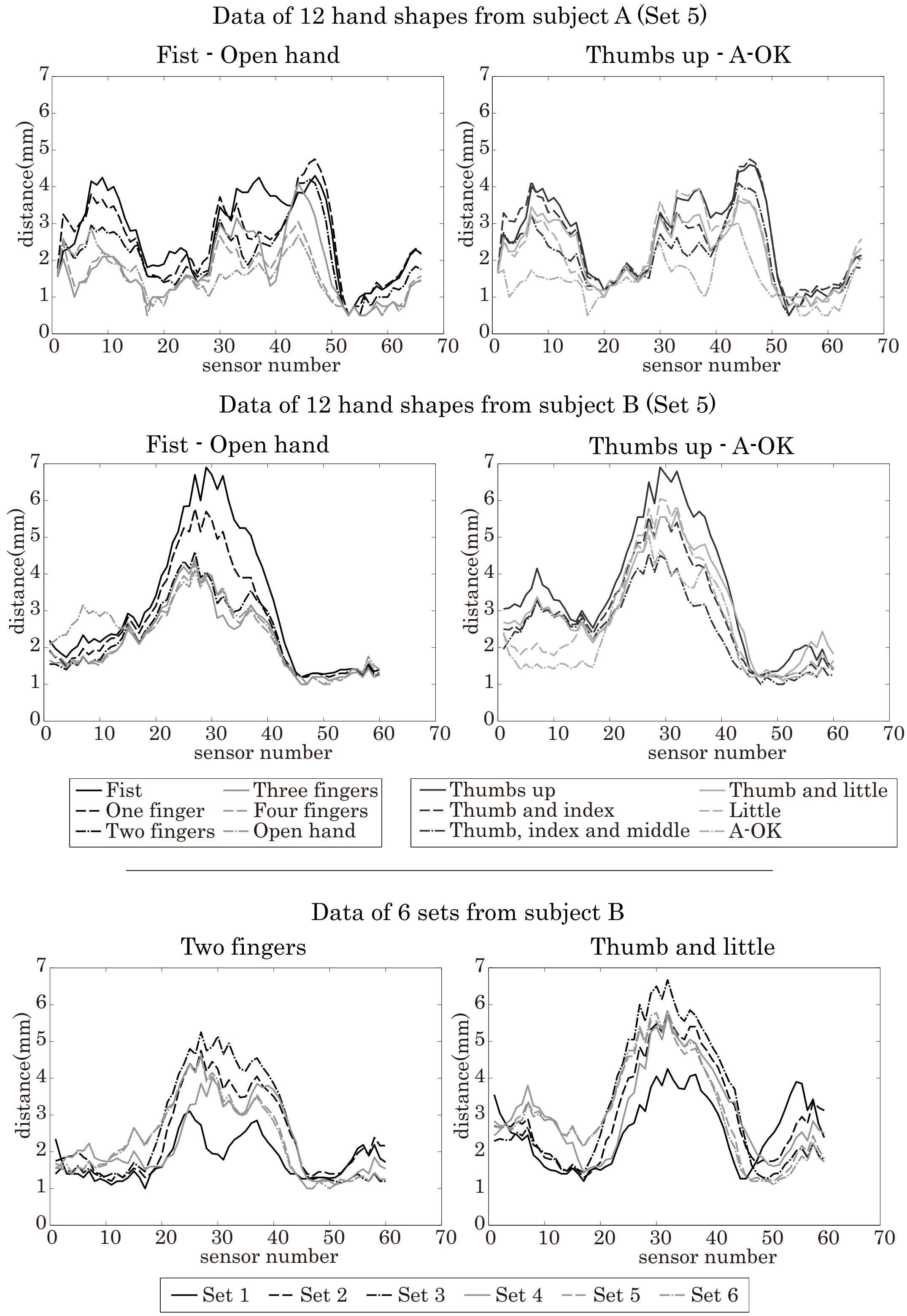
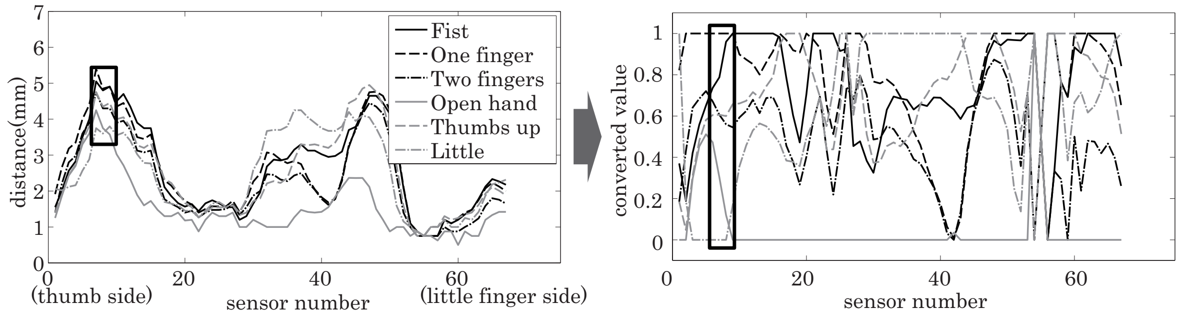


Figure 8: Examples of wrist contour data.



The boxed data are emphasized through normalization.

Figure 9: Example of wrist contour normalization.

Open hand difference histogram is the most complicated statistics. The calculation procedure of the histogram is as follows. With the wrist contour raw data (Figure 10), differences from Open hand data of the same set are calculated (Figure 11), and then the histogram of 16 bins are made (Figure 12).

$$Wrist\ contour\ data: \quad \boldsymbol{x} = [x_1, \ldots, x_i, \ldots, x_N] \tag{1}$$

$$Sum\ of\ distances: \quad \phi = \textstyle\sum_{i=1}^{N} x_i \tag{2}$$

$$Sum\ of\ differences: \quad \phi = \textstyle\sum_{i=1}^{N-1} |x_{i+1} - x_i| \tag{3}$$

$$Ratio\ of\ former\ half\ sum\ and\ latter\ half\ sum: \quad \phi = \frac{\sum_{i=1}^{N/2} x_i}{\sum_{i=N/2+1}^{N} x_i} \tag{4}$$

$$Max\ monotone\ increment\ value: \quad \phi = max_{j,k}(x_{p_j} - x_{v_k}), while\ p_j < v_k < p_{j+1} \tag{5}$$

$$(\boldsymbol{p} : peak\ points\ of\ x, \boldsymbol{v} : valley\ points\ of\ x)$$

$$Score\ of\ open\text{-}hand\ difference\ histogram: \quad \phi = \textstyle\sum_{l=1}^{16} |b_{y,l} - b_{Fist,l}| \tag{6}$$

$$(b_{y,l} : number\ of\ points\ in\ the\ lth\ bin\ of\ hand\ shape\ y)$$

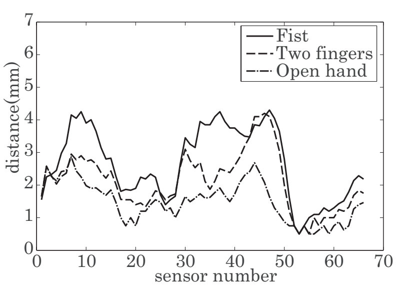


Figure 10: Wrist contour data of two hand shapes (Fist and Two fingers) and Open hand.

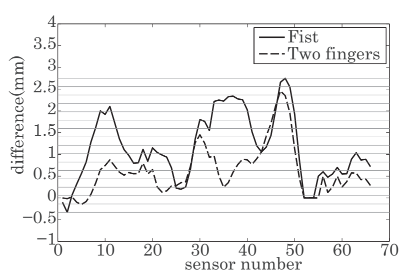


Figure 11: Differences between the data of two hand shapes and the data of Open hand.

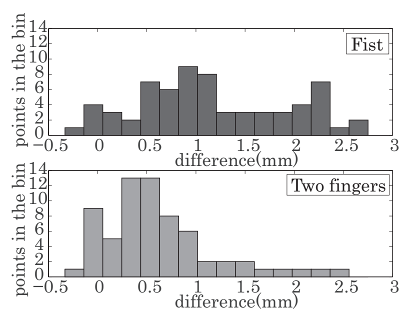


Figure 12: Histograms of open-hand differences of two hand shapes.

5.2 Classification methods

As classification methods, two machine learning methods are used.

One is k-Nearest Neighbor (k-NN) method. In the k-NN method, the test sample is labeled by the votes of k nearest samples. All Euclidean distances between a test sample and training samples in the feature space are calculated, and nearest k training samples have rights to vote as a classification result.

The other is AdaBoost [10]. AdaBoost is a kind of boosting method, which makes some weak learners (in this paper, decision stump). The test sample is labeled by weak learners' weighted votes. Weights on weak learners are tuned to fit to training data in the training process.

6 EXPERIMENT 1

The purpose of this experiment is to compare classification performance with different feature types.

6.1 Settings

Classification performance is evaluated by classification rate (number of correct samples / number of all samples). Six hand shape classes (Fist, Thumbs up, Little, One finger, Two fingers Open hand) are selected as recognition targets. They are empirically selected considering that they are easily imitated by subjects and they have relative unique features in wrist contours. As for features, two feature types and one extended feature type are compared.

A. Normalized contour data : 45 dimensions.

All contour data are linearly converted to the smallest wrist contour size (45 sensor elements). The data of only one array nearer to hand are used because a prior experiment[1] shows that the performance using one array is better than the one using two arrays.

B. Contour statistics : 92 dimensions.

46 statistics $\times$ 2 arrays.

C. Selected contour statistics : 5 dimensions.

This feature type is extended from feature type B. When classifying with contour statistics and k-NN method, it might exert dramatically low performance because each statistics has the same weight. In addition, when classifying using AdaBoost, over-fitting might occur because of the small number of samples. Hence, we designed another feature type of only 5 contour statistics that have the highest separation metrics. The separation metric is calculated as inter-class variance divided by in-class variance.

Classification methods are k-NN method and AdaBoost method. As for training data, three groups are prepared. These groups are selected to evaluate the robustness against individual differences.

[1] We conduct prior experiment with the data from 5 subjects. Settings are as follows; 5 subjects, training group 1, k-NN method. The classification rates when using hand-side array, elbow-side array, both arrays are 85.6%, 78.9%, 82.2%.

Group 1. Subject's own data 5 sets.

Group 2. Subject's own data 5 sets and other subjects' 27×6 sets: 167 sets in total.

Group 3. Other subjects' 27×6 sets: 162 sets in total.

We use cross-validation to evaluate each training groups. Except for the test data set/subject, all data sets are used for training of classifier.

6.2 Results

Figure 13 shows the experimental results. As expected, the combination of feature type B and k-NN method exerts low score in all groups. When classifying using group 1 with AdaBoost, low scores indicate that over-fitting occurs because of small number of training samples. In group 1 (the subject's own data), feature type A exerts higher performance in classification rate than feature type B and C. The combination of normalized contour data and k-NN method exerts the highest classification rate of 90.1 %. In group 2 (the subject's own data and other subjects' data), no remarkable difference is observed among three feature types. In group 3 (other subjects' data), feature type B and C exert better performance than feature type A. The combination of contour statistics and AdaBoost exerts the best classification rate of 78.4 %. Figure 14 shows the confusion matrix when classifying using group 1 with normalized contour data and k-NN method. High classification rates are observed for almost all hand shapes, however, a little confusion between Fist and Little is observable. And Figure 15 shows the confusion matrix when classifying using group 3 with contour statistics and AdaBoost. There is some confusion among similar hand shapes. For example, hand samples that have one stretching finger from Fist (Thumbs up, Little and One finger) are confused, and hand shapes that have difference with only one finger (One finger and Two fingers) are also confused.

6.3 Discussion

As for feature types, it is confirmed that effective features are different according to training data group. Specifically, in the classification of 6 hand shapes, normalized contour data exert high classification rate of 90.1 % with k-NN method when using subject's own data as training data. Therefore, local variations are important to extract wrist contour variation in one subject for hand shape recognition. If a user has enough time to accumulate many training data, the combination can be a solid candidate for a recognition process.

On the other hand, when using only other subjects' data as training data, contour statistics exert the best classification rate of 78.4 % with AdaBoost. Consequently, the features common in all subjects are statistics of whole wrist contour data rather than local variation of them. The weights of AdaBoost weak learners indicate that effective statistics are as follows; Open hand difference histogram score, Sum of distances, Ratio of former sum and latter sum, Sum of differences, Maximum monotone increasing

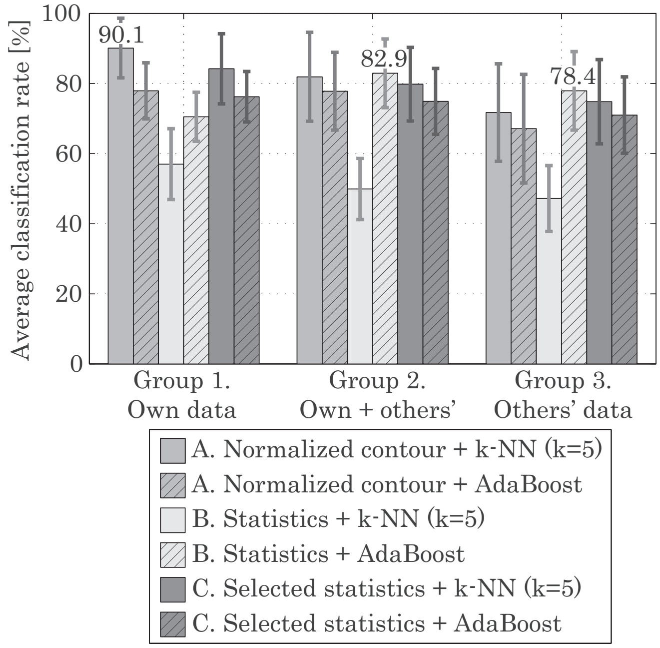


Figure 13: Results of experiment 1.

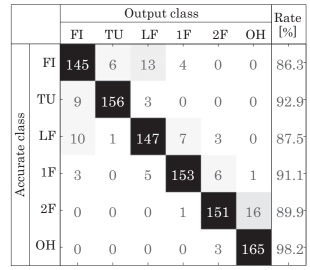


Figure 14: Confusion matrix of group 1 with A and k-NN.

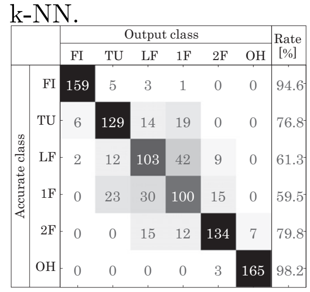


Figure 15: Confusion matrix of group 3 with B and AdaBoost.

value.

Even though the effective features differ according to the target properties of hand shape, we obtained clues how to select or design features.

7 EXPERIMENT 2

The purpose of this experiment is to compare classification performance with different target properties of hand shape.

7.1 Settings

As for the combination of feature type and classification method, we use feature type A with k-NN method and feature type B with AdaBoost, which exert high score in each training group of experiment 1. Group 3 in the previous section (other subjects' data 27×6 sets: 162 sets in total) is selected as training data group, because calibration process should be concise enough for a new user in practical use. The numbers of hand shapes in combinations are 4, 6, 8 and 12. In each combination, Fist and Open hand are fixed for calibration. We configure 14 combinations (4 classes: 7 combinations, 6 classes: 4 combinations, 8 classes: 2 combinations, 12 classes: 1 combination). The selection of combinations is based on our practical experiences, because it takes too much calculation time to evaluate all combinations. For example, 4 classes have 45 variations, 6 and 8 classes have both 210 variations. It takes about 4,200 hours to calculate all combinations for 8 classes.

7.2 Results

Figure 16 shows the experimental results. As for the feature type and classification method, contour statistics with AdaBoost exerted higher score in 13 hand shape combinations, and normalized contour data with k-NN method exerted higher score only in one combination (12 classes). The classification rate values in Figure 16 are the higher score in two feature types and classification methods. It is revealed that the classification rates are decreasing in proportion to the number of target hand shapes increasing. In the combinations of the same number of targets, the classification rate substantially differs according to the combination. For example, difference between 4a and 4g is 17.1 % and difference between 6a and 6d is 12.5 %.

Figure 17 shows confusion matrices of all combinations of 4 classes. Along with the results of experiment 1, there is some confusion among similar hand shapes. For example, hand shapes that have one finger stretching from Fist (Thumbs up, One finger) are confused, and hand shapes that have difference with only one finger (One finger and Two fingers, Two fingers and Thumb, index and middle) are also confused.

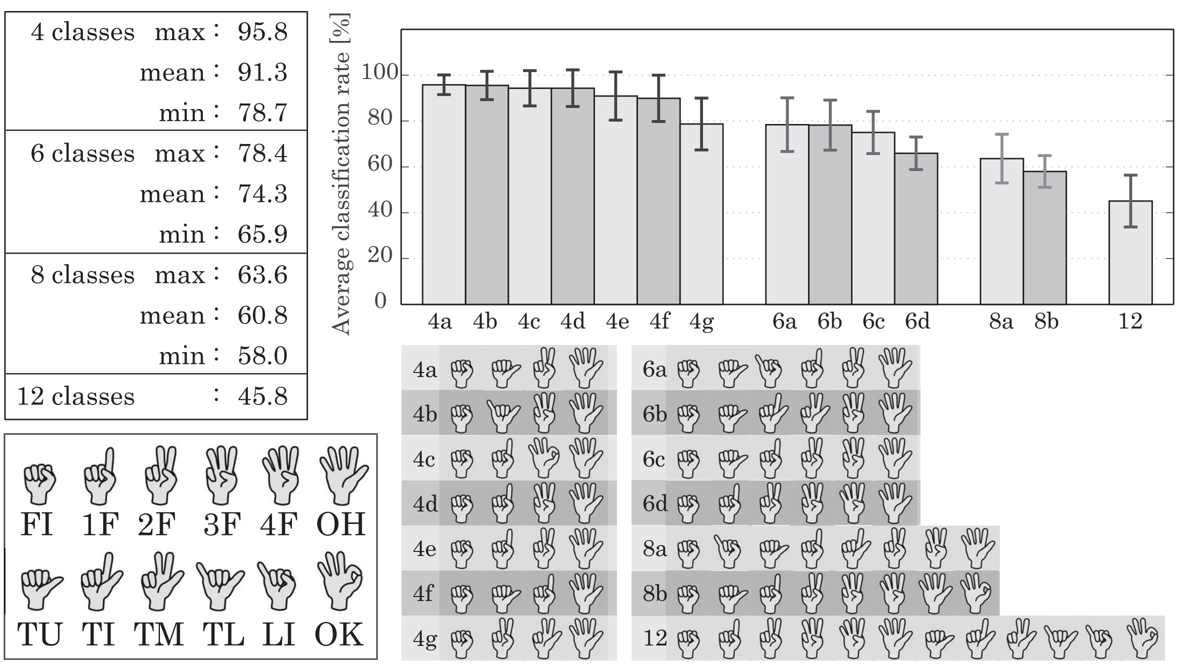
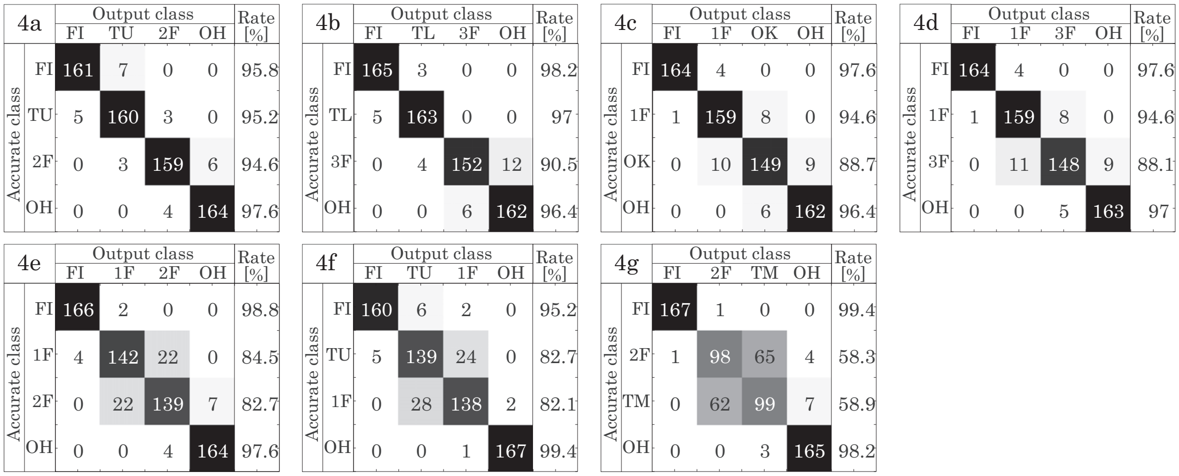


Figure 16: Results of experiment 2.



4a	FI	TU	2F	OH	Rate [%]
FI	161	7	0	0	95.8
TU	5	160	3	0	95.2
2F	0	3	159	6	94.6
OH	0	0	4	164	97.6

4b	FI	TL	3F	OH	Rate [%]
FI	165	3	0	0	98.2
TL	5	163	0	0	97
3F	0	4	152	12	90.5
OH	0	0	6	162	96.4

4c	FI	1F	OK	OH	Rate [%]
FI	164	4	0	0	97.6
1F	1	159	8	0	94.6
OK	0	10	149	9	88.7
OH	0	0	6	162	96.4

4d	FI	1F	3F	OH	Rate [%]
FI	164	4	0	0	97.6
1F	1	159	8	0	94.6
3F	0	11	148	9	88.1
OH	0	0	5	163	97

4e	FI	1F	2F	OH	Rate [%]
FI	166	2	0	0	98.8
1F	4	142	22	0	84.5
2F	0	22	139	7	82.7
OH	0	0	4	164	97.6

4f	FI	TU	1F	OH	Rate [%]
FI	160	6	2	0	95.2
TU	5	139	24	0	82.7
1F	0	28	138	2	82.1
OH	0	0	1	167	99.4

4g	FI	2F	TM	OH	Rate [%]
FI	167	1	0	0	99.4
2F	1	98	65	4	58.3
TM	0	62	99	7	58.9
OH	0	0	3	165	98.2

Figure 17: Confusion matrices of 7 combinations (4 classes).

7.3 Discussion

It is confirmed that the classification performance gets worse as the number of target hand shapes increases. Considering practical use, the combinations of 4 target hand shapes exert enough classification rates of over 90 % in current features and methods. Even in the same number of target hand shapes, the performance varies according to the combinations. Consequently, a certain combination might be more difficult classification task than a combination of larger number of target hand shapes.

We analyze more deeply about the difference of the recognition difficulty in target combinations based on the results of 4 target hand shapes. In 7 combinations of 4 targets, the best is 4a and the second is 4b, the worst is 4g. Focusing on the classification rate of each hand shape, Fist and Open hand remark high performance because they are used as calibration data. Therefore, the confusion between the other two hand shapes determines the classification performance. Here, to represent the hand shape in numerical values, we convert the finger bending and stretching into a binary datum {0, 1}. And then a hand shape is represented as binary data of five dimensions (e.g. Two fingers is [0, 1, 1, 0, 0], Little is [0, 0, 0, 0, 1]). The difference between two hand shapes is represented as a Hamming distance (e.g. the Hamming distance between Two fingers and Little is 3). Intuitively, the larger Hamming distance between hand shapes, the easier the classification becomes. Figure 18 shows the relationships between the Hamming distance of two hand shapes (other than Fist and Open hand) and the classification rate in 7 combinations of 4 target hand shapes. We can see that classification rates are in subtle proportion to Hamming distances. Especially, confining to index and middle fingers, which have thick muscles, the classification rate is obviously proportional to Hamming distances of two fingers as shown in Figure 19. The facts can be clues to find a combination of independent hand shapes.

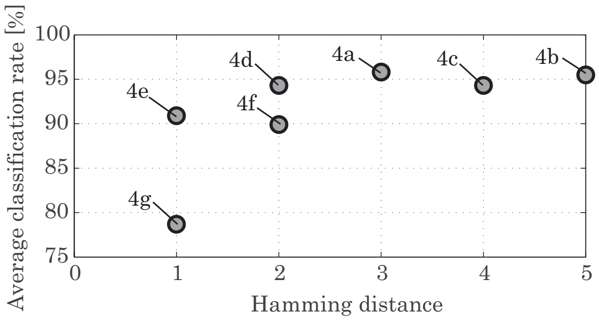


Figure 18: Relationships between classification rate and hamming distance of all fingers.

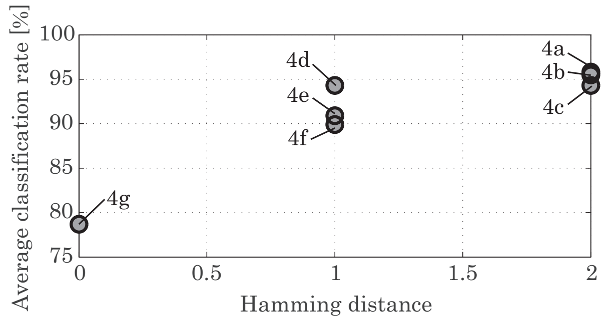


Figure 19: Relationships between classification rate and hamming distance of index and middle fingers.

8 CONCLUSIONS and FUTURE WORK

8.1 Conclusions

As for the three challenges in section 2, our contributions are as follows.

1. We developed a wrist-watch-type device to measure wrist contours. To make the device stable and robust, we adopt shift registers to switch outputs of the photo reflectors mounted on the measurement band. In addition, the fixing band is appended to improve wearability and reduce slippage. With the developed device, we collected wrist contour data from substantial number of subjects. It is confirmed that wrist contours differ not only with hand shapes but also with attaching positions or individuals.

We conducted two types of hand shape classification experiments using the collected wrist contour data.

2. Experiment 1 was intended to compare the feature types. We designed and compared two feature types; normalized contour data and contour statistics. It was found out that normalized contour data performs well when using subject's own data as training data and contour statistics performs well when using other subjects' data as training data. As for contour statistics, it is indicated that the effective statistics are Open hand difference histogram score, Sum of distances, Ratio of former sum and latter sum.

3. Experiment 2 was intended to find the target properties of the hand shapes classification. It is confirmed that classification performance decreases as the number of target hand shape increases. However, even in the same number of targets, the combinations affect the classification performance considerably. One clue to find a combination of individual hand shapes is the difference of bending and stretching of fingers (especially index and middle fingers).

8.2 Future work

We have three assignments as future work.

First, confining to using only other subjects' data, enough performance of 95.8 % is achieved in 4 target hand shapes. However, in larger number of targets, the performance is not enough for practical use (78.4

% in 6 target hand shapes). Because the large number of target hand shapes expands applications, we need to improve more than 4 class recognition for practical use. Promising solutions are design of new features and selection of training data. In addition, the combination of hand shapes can be selected based on the recognition performance.

Second, it is necessary to deal with the wrist pronation. In this paper, arm posture is fixed to prevent from wrist contour variations caused by wrist pronation. It will be a barrier when combining hand shape recognition and other gestures. Promising solutions to deal with wrist pronation changes are increment of classes combining pronation, and sensing of pronation with additional sensor such as an accelerometer.

Third, miniaturization and integration of the device are required. The current device has a slightly big wireless module and a battery to ensure the stability and reliability. To avoid interference with hand motions, those big elements are separated from the wrist. However, to improve the convenience and reduce restraints, a wrist-integrated device is desirable. We will use a smaller wireless module and a battery and realize a wrist-integrated device without reducing stability and reliability.

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APPENDIX

A WRIST CONTOUR DATASET

Readers can download the wrist contour dataset from our web site; http://www.ics.t.u-tokyo.ac.jp/index.html As described in section 4, this dataset includes the wrist contour data of 6 sets of 12 hand shapes from 28 subjects. The total amount of data is 2,016. Supplementary information is as follows.

- The measurement band is fixed by the holes in the band and the pins on the measurement part. The pitch of the holes is 7 mm and the size of wrist circumference is recorded as the hole index.
- The subjects are from 20's to 50's, mainly 20's.
- The subjects are 25 males and 3 females.