

Hand Shape Classification with a Wrist Contour Sensor: Development of a Prototype Device

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ABSTRACT

In this paper, we describe a novel sensor device which recognizes hand shapes using wrist contours. Although hand shapes can express various meanings with small gestures, utilization of hand shapes as an interface is rare in domestic use. That is because a concise recognition method has not been established. To recognize hand shapes anywhere with no stress on the user, we developed a wearable wrist contour sensor device and a recognition system. In the system, features, such as sum of gaps, were extracted from wrist contours. We conducted a classification test of eight hand shapes, and realized approximately 70% classification rate.

Author Keywords

Hand shape recognition, classification, wrist contour, gesture interface.

ACM Classification Keywords

H.5.2 User Interfaces: Input devices and strategies.

General Terms

Design, Experimentation, Measurement.

INTRODUCTION

Increasing numbers of companies and researchers are developing natural user interfaces using gestures for human computer interaction[1]. Prominent examples are TV game interfaces such as Wii (Nintendo) and Kinect (Microsoft). Their success made gesture recognition interfaces popular. The most common action used in gesture interfaces is arm movement. However, it requires substantial physical energy and lacks the ability of precise expression. Therefore in this study, we put focus on hand shapes. Hand shapes are used in many scenes such as hand language or hand signals, and we presume that hand shapes are good gestures which can express much information with small actions. Nevertheless,

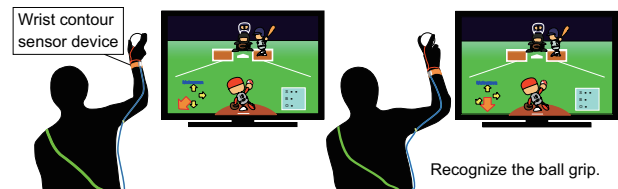


Figure 1. TV game with wrist contour sensor device.

there are few examples using hand shape recognitions in domestic use because a concise recognition method has not been established yet. There are several hand shape recognition methods[5]; we discuss the features and problems of some major methodologies hereafter.

Wired glove[3]: A wired glove is a glove-like input device that captures the finger bending with sensors mounted on the finger joints. It disturbs the haptic sense of the hand because the glove covers over a whole hand.

Electromyogram signals[6]: Signals are captured by wet or dry type electrodes attached to the surface of the forearm, and the electro signals are used for recognition. Because it is unnecessary to attach a device to a hand, the influence on hand movements is little. However, the electrodes must cover the whole forearm, and it is necessary to compress the arm for reducing the clearance between the electrode and the arm surface. Thus, the stress on the user is a problem.

Camera[4][9]: It trims the hand area from captured images and recognizes the hand shape. It does not disturb the activity and does not stress the user. However, the whole hand must be in the camera view range.

Therefore existing methods may be problematic for domestic use. These problems include the influence on activity, stress on the user, and limitation of circumstances. In this study, we propose the use of "wrist contours" for hand shape recognition. Rekimoto [7] measured wrist contours by capacitive sensors and recognized two hand shapes. We developed a new device using another type of sensor, and it can measure wrist contours more precisely. Figure 1 is a conceptual image of a game interface application. It will capture the ball grip, which any existing interfaces cannot get, and allows players to express a throwing motion more naturally.

WRIST CONTOUR BASIS

We designate a wrist cross-section contour (especially a wrist circumference contour near ulna) as a wrist contour. Figure 2

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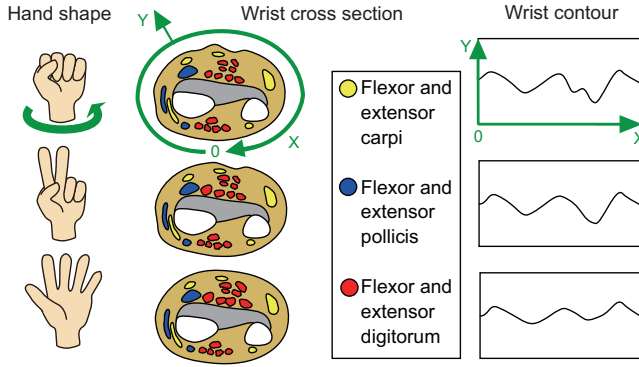


Figure 2. Wrist contour basis.

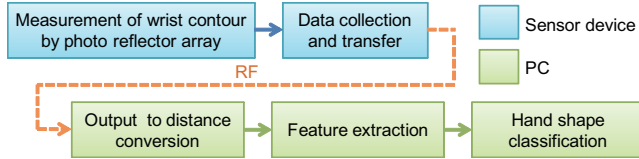


Figure 3. Data flow block diagram.

shows examples of hand shapes and wrist contour sets. Muscles and tendons for finger movements are compacted near the elbow. Around the wrist, however, tendons and muscles are separated to some extent, so they are comparatively observable. We observed the variation of their thicknesses and positions, which vary with finger movements. For example, to bend a finger, a flexor contracts and the nearby wrist surface dents. To straighten a finger, a flexor relaxes and the nearby wrist surface becomes as before. Our approach is to recognize hand shapes from these variations.

WRIST CONTOUR MEASURING SYSTEM

Figure 3 shows our system configuration and data flow diagram. We developed a wrist watch type sensor device (Figure 4) and a recognition system.

Required specification

Human constraints and our design are as follows.

• Human constraints:

- (1a) Muscles and tendons for finger movements are approximately 5 mm in diameter.
- (1b) Radial variation of wrist contour is approximately 5 mm at maximum.
- (2a) Wrist circumference is approximately 150~170 mm.
- (2b) Human arm motions should not be interrupted.

• Design:

- (1a) Sensor pitch is 2.5 mm around circumference.
 - (1b) Radial resolution of the sensors is 0.1 mm.
 - (2a) Measurement area is at least 170 mm in circumference.
 - (2b) The band is narrower than 30 mm.
- To achieve the design requirements, we adopted photo reflector sensors and shift register switching method.

Photo reflector as distance sensor

Photo reflector is a combination of infrared LED and photo transistor. LED transmits an infrared signal and Photo tran-

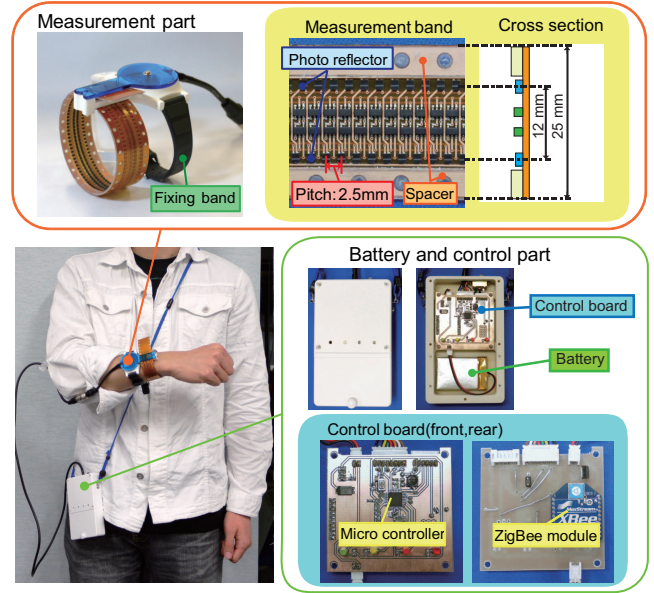


Figure 4. Wrist contour measuring device.

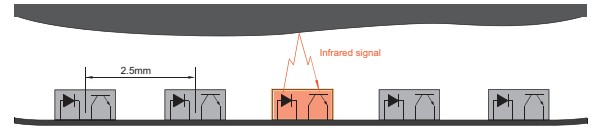


Figure 5. Mechanism of photo reflector.

sistor detects the intensity of the signal reflected at the surface of the object as shown in Figure 5. We selected a small photo reflector sensor "NJL5901AR-1" (produced by New Japan Radio Co.) to achieve the measurement density 2.5mm. Because an output of photo reflector is non-linear with distance, and sensors have individual differences, raw outputs cannot be used for measuring distances as they are. Then, we calibrated the outputs by prior measurement. We measured range of 0~10mm with 0.05mm pitch with 1-axis automatic stage to achieve 0.1mm radial resolution. As a result, we achieved 0.1mm resolution in 0~3.5mm. As figure 6 indicates, the smooth surface of an inclined flat board can be recognized in the range of 0~3.5mm.

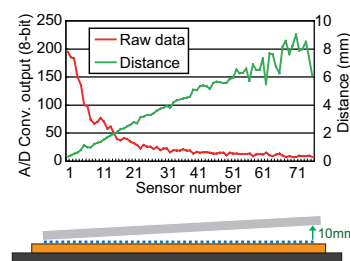


Figure 6. Measuring an inclined board.

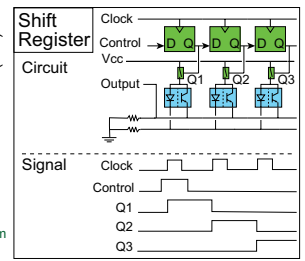


Figure 7. Shift register switching method.

Shift register switching method

To measure the whole circumference of wrist contours, we arranged photo reflector sensors in rows. We mounted them

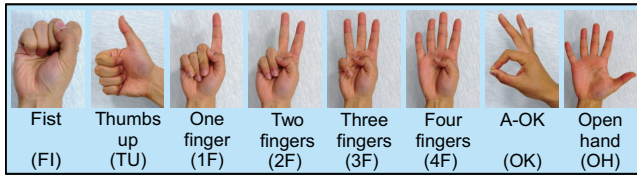


Figure 8. Hand shape eight classes.

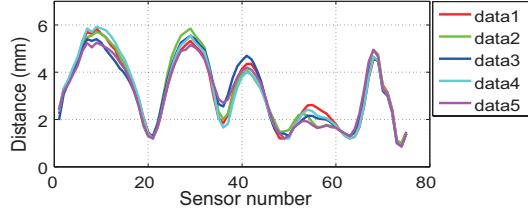


Figure 9. Five data at the same attachment condition.

on a flexible printed circuit board (measuring band). There are two rows in both side of the band and each row has 75 sensors in 2.5mm pitches, so the total number of sensors is 150 and measurement length is 185mm. In this configuration, if all sensors are controlled by one unit, it needs numerous number of signal lines and they make the band wider. Therefore, we utilized the shift register switching method as shown in Figure 7. The D-flip-flops and analog switches realize a sequential measurement by just sending trigger signals. That means only one sensor is active at once.

ANALYSIS OF WRIST CONTOUR

We collected wrist contour data from ten subjects with the device. Subjects are all students, and the wrist device was attached to the right hand. When putting the device on, subjects are guided by an experimenter, but the device is attached by themselves. The device was reattached each time we collected data. We configured eight hand shape classes as shown in Figure 8 and observed differences based on hand shapes, individuals, arm postures and so on. Figure 9 is sample data of one subject, fist class, five iterations, and without reattachment. We confirmed repeatability in the same class and the same posture when the identical subject did not reattach the device.

Individual differences

Figure 10 shows wrist contour data of three hand classes of two subjects. The graph indicates that wrist contours vary not only with hand shapes but also subjects.

Introduction of feature extraction

Variation between subjects executing the same hand shape was large compared with a subject's variation of the contour between hand shapes. So it is difficult to classify using subject-independent models on the raw data. We solved this assignment by introduction of feature extraction.

HAND SHAPE CLASSIFICATION

We didn't adopt regression between finger joint angle and outputs but classification of hand shape. That is because

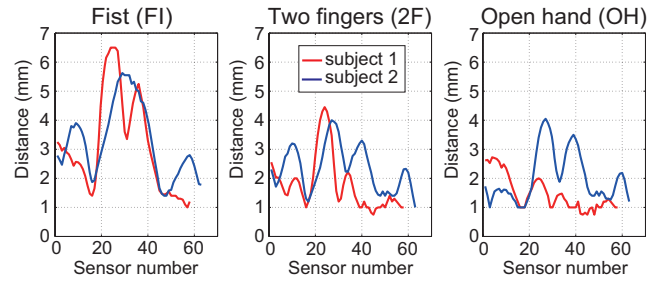


Figure 10. Three hand shape classes of two subjects

Single feature	Sep. Met.	Adopted features are colored.	
Sum of gaps	3.104	Differences* of Diff-hist	0.795
Sum of neighbours differences	0.575	Sum ratio (former/latter)	0.020
Number of maximal points	0.042	Max increment width	0.052
Number of minimal points	0.024	Max increment value	0.514
Max gap	0.581	Max decrement width	0.039
Min gap	0.377	Max decrement value	0.320
Differences* of Gap-hist	1.522	*Sum of differences between bins of the class and that of fist class	
Histogram feature	Num. of bin	Sep. Met. (Ave.)	
Gap Histogram (Gap-hist)	8	0.190	
Difference of neighbours histogram (Diff-hist)	8	0.110	
Open hand difference histogram	16	0.497	

Table 1. Separation metrics of features

muscles and tendons for finger movements are crowded even near the wrist, and it is difficult to recognize the wrist contour variation of independent finger.

Feature extraction

We organized feature candidates (13 single features and 3 histogram features), and evaluated their availabilities. Data of fist class and open hand class were used as the pre-classification calibration data. In evaluation of features, we used separation metrics as an evaluation standard.

$$\text{Separation metrics} = \frac{\text{Between class variance}}{\text{Within class variance}}$$

We can evaluate effectiveness of features without learning process with the metrics value. Table 1 shows feature candidates and separation metrics of them. Through this analysis, we selected six single features and one histogram feature with high separation metrics. Figure 11 shows the overview and chart of one good feature; max increment value.

Classification method

We designed a classification method using the features as inputs.

Target hand shape classes are eight classes as shown in Figure 8. We utilized "k-NN method", which can use data similarity effectively, and "boosting", which can make strong classification from weak features [2]. As for boosting, we utilized multi-class method Adaboost.MH [8] with weak learners of features. Each feature is normalized from the calibration data of fist and open hand class, eventually the range between max and min was configured to 2.0.

EXPERIMENT

We conducted hand shape classification experiments. The classification outputs the most probable class. Experiments are sorted into two categories: (1) learning data including

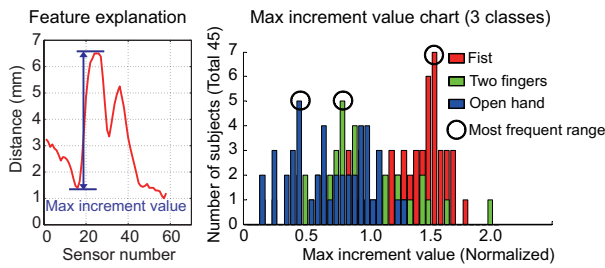


Figure 11. Feature example (max increment value)

the subject's data and (2) learning data excluding the subject's data. In category (1), three data were used for learning and another data was used for test regarding the subject. Learning data included three data of the other six subjects. In category (2), we exerted cross-validation: nine subjects' data out of ten subjects' data were used for learning data and one subject's data was used for test data in rotation.

Figure 12 and Figure 13 show the experimental results. Row classes are input classes (answer classes) and column classes are output classes. The diagonal line indicates correct output classes, larger numbers on the diagonal line mean better performance of the classification. The performance was evaluated in classification rate.

$$\text{Classification rate} = \frac{\text{Number of correct samples}}{\text{Number of all samples}}$$

The classification rate (Boosting, k-NN method) are 64.1%, 72.2% in category (1) and 47.8%, 45.6% in category (2). However, in category (2), classification rate changed from 35.8% to 65.4% (Boosting) and from 25.4% to 59.6% (k-NN method) depending on the combination of the data. We thought this is because subjects who have similar wrist contours are exist and high classification rate occurs when one subject is assigned to learning data and the other is assigned to test data. So collecting more learning data may enhance the performance of the classification.

CONCLUSIONS

In this study, we developed a novel hand shape classification system using wrist contours in order to recognize hand shapes with little stress on users.

First, we developed a wrist-watch type wrist contour sensor device. Mounting small distance sensors (photo reflectors) on a flexible band enabled to measure wrist contour with 2.5mm pitch. Second, we observed differences attributed by hand shapes and postures, and then picked up some useful features such as sum of gaps and differences of histogram. In classification, approximately 70% classification rate was marked when the learning data included the subject's data. Additionally, it was confirmed that some subjects have similar wrist contour and it indicates the possibility of pre-learning-free recognition.

REFERENCES

1. M. Baldauf et al. Gestural interfaces for micro projector-based mobile phone applications. In *Proc. of the Int. Conf. on Ubiquitous Computing*, 2009.
2. C. M. Bishop. *Pattern Recognition and Machine*

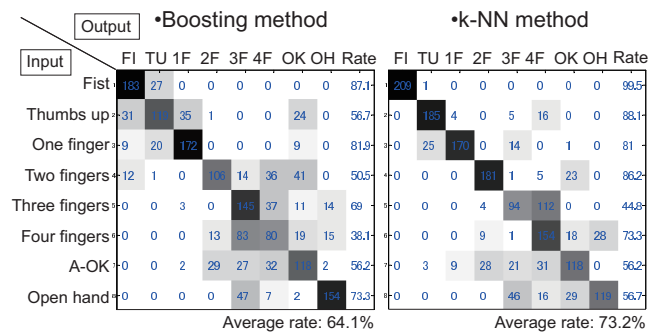


Figure 12. Results 1 (Including subject's data)

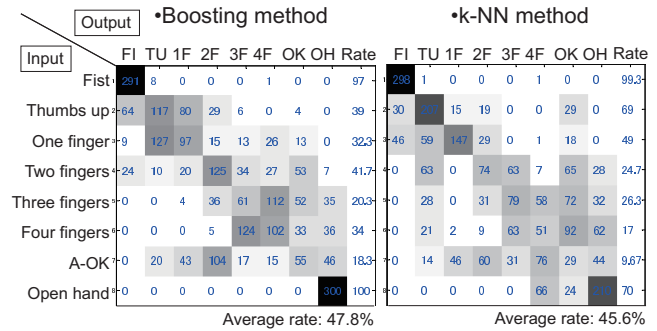


Figure 13. Results 2 (Excluding subject's data)

Learning (Information Science and Statistics). Springer, 1st ed. 2006. corr. 2nd printing edition, 2007.

3. CyberGloveSystems.
<http://www.cyberglovesystems.com/>.
4. A. Erol et al. A review on vision-based full dof hand motion estimation. In *Proc. of IEEE Computer Society Conf. on Computer Vision and Pattern Recognition*, page 75, 2005.
5. T. S. Huang et al. Hand gesture modeling, analysis, and synthesis. In *Proc. of IEEE Int. Workshop on Automatic Face and Gesture Recognition*, pages 73–79, 1995.
6. K. Nagata et al. A classification method of hand movements using multi channel electrode. In *Proc. of IEEE-EMBS. Annual Int. Conf. of the Engineering in Medicine and Biology Society*, pages 2375–2378, 2005.
7. J. Rekimoto. Gesturewrist and gesturepad: Unobtrusive wearable interaction devices. In *Proc. of the 5th IEEE International Symposium on Wearable Computers*, IEEE Computer Society Washington, DC, USA, 2001.
8. R. E. Schapire et al. Improved boosting algorithms using confidence-rated predictions. *Machine Learning*, 37:297–336, 1999.
9. T. Starner et al. Real-time american sign language recognition using desk and wearable computer based video. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 20(12):1371–1375, 1998.