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Hand shape classification in various pronation angles using a wearable wrist contour sensor

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Hand gestures are potentially useful for communications between humans and between a human and a machine. However, existing methods entail several problems for practical use. We have proposed an approach to hand shape recognition based on wrist contour measurement. Especially in this paper, two assignments are addressed. First is the development of a new sensing device in which all elements are installed in a wrist-watch-type device. Second is the development of a new hand shape classifier that can accommodate pronation angle changes. The developed sensing device enables wrist contour data collection under conditions in which the pronation angle varies. The classifier recognizes the hand shape based on statistics produced through data forming and statistics conversion processes. The most important result is that no large difference exists between classification rates that include or those that exclude the independent (preliminary) pronation estimation process using inertia measurement units. This result shows two possible insights: (1) the wrist contour has some features that depend on the hand shape but which do not depend on the pronation angle, or (2) the wrist contour potentially includes pronation angle variation information. These insights indicate the possibility that hand shape can be recognized solely from the wrist contour, even while changing the pronation angle.

Keywords: wearable sensor; user interface; hand shape recognition; wrist contour; unobtrusive device

1. Introduction

Hand gestures can potentially express rich information with small motions for communication between humans and between a human and a machine. Various related works have been conducted to use hand gestures for human–machine interfaces. These works are divisible into three categories: (A) Glove-type methods [1,2], (B) Electromyography methods [3,4], and (C) Camera methods [5–8]. However, as Table 1 shows, these methods entail multiple difficulties such as recognition accuracy, interference on activity, troublesome setup processes, mobility, and cost-performance.

In our previous work [9], we developed a wearable wrist contour sensor that recognizes hand shape with substantial accuracy merely by measuring the surface contour of the human wrist. The most severe problem of the developed device was that it cannot accommodate pronation angle change, which means that a user of this device must fix the forearm while using the device. This constraint reduced its usability considerably. In addition, the device was separated into two parts: a wrist-watch-type measurement part and a pouch-type control part. This configuration reduced wearability.

This paper specifically addresses two assignments: (1) development of a new sensing device in which all elements are installed in a wrist-watch-type device, and (2) development of a new hand shape classifier that can accept pronation angle change. Especially in the second assignment, we aim to reveal whether an independent (preliminary) process to estimate the pronation angle is necessary for accurate hand shape classification or not. To tackle this assignment, this paper compares two methods. One method uses inertia measurement units (IMUs) for independent estimation of the pronation angle. The other method uses only the wrist contour sensor to estimate the hand shape directly.

Section 2 of this paper presents the basis of wrist contour variations, stem from the hand shape transition, and explains methods to measure the wrist contour and the pronation angle. Section 3 presents an overview of the newly developed wrist-watch-type device. Section 4 describes data collection using the developed device and analyses of those collected wrist contour data. Section 5 explains our hand shape classification experiment, in which participants need not fix a pronation angle, which is the major point of
Table 1. Comparison of related works.

<table>
<thead>
<tr>
<th>Approach</th>
<th>Accuracy</th>
<th>Unobtrusiveness to body motion</th>
<th>Interference to haptic sense</th>
<th>Mobility</th>
<th>Conciseness of initial setup</th>
<th>Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data glove</td>
<td>High</td>
<td>★★★</td>
<td>★</td>
<td>★★★★</td>
<td>★</td>
<td>★★★★</td>
</tr>
<tr>
<td>EMG</td>
<td>Low</td>
<td>★</td>
<td>★</td>
<td>★★★★</td>
<td>★</td>
<td>Medium</td>
</tr>
<tr>
<td>Camera (Fixed)</td>
<td>★★★</td>
<td>★</td>
<td>★</td>
<td>★★★</td>
<td>★</td>
<td>★★★★</td>
</tr>
<tr>
<td>Camera (Wearable)</td>
<td>Medium</td>
<td>★</td>
<td>★</td>
<td>★★★</td>
<td>★</td>
<td>★★★★</td>
</tr>
<tr>
<td>Our method (Potential)</td>
<td>Medium</td>
<td>★</td>
<td>★</td>
<td>★★★</td>
<td>★</td>
<td>★★★★</td>
</tr>
<tr>
<td>Our method (Current)</td>
<td>Low</td>
<td>★</td>
<td>★</td>
<td>★★★</td>
<td>★</td>
<td>★★★★</td>
</tr>
</tbody>
</table>

difference from our previous work. Section 6 presents important conclusions.

2. Hand shape classification using a wearable wrist contour sensor

This section describes the basis of wrist contour variations and explains methods to measure the wrist contour and pronation angle.

2.1. Basis of wrist contour variations

The wrist contour is the surface contour around the human wrist. This contour varies with the motion of tendons and muscles in the forearm. Figure 1 portrays a cross-section view of a wrist and describes how tendons, muscles, and bones are moved by the changing hand shape. Regarding the tendons and muscles used for finger motion, flexors are located in the palmar side of the hand. Extensors are located in the dorsal side of the hand [10]. These tendons and muscles are compacted near the elbow, but they branch to some degree around the wrist. Movement of fingers brings position and thickness changes of tendons and muscles. Consequently, the surface contour of the wrist varies. This variation enables estimation of the hand shape.

If muscles and tendons exist in a completely separated condition in the wrist, it is possible to estimate the motion of each finger independently. However, they overlap in fact. Therefore, this study, instead of estimating each finger motion, estimates the hand shape. Figure 2 shows how the positions of tendons and muscles change depending on the pronation angle. The wrist contour varies not only by the hand shape but also by the pronation angle change. The forearm posture is also changed by the extension and contraction motion of arm and is changed by shoulder motion, but our experience has confirmed that these motions do not strongly influence the wrist contour.

Figure 1. Muscles in the wrist and wrist contour variations.

Figure 2. Wrist contour variation deriving from pronation angle change.
two phenomena simultaneously: (1) the variations of wrist surface contour derived from the hand shape and pronation angle changes, and (2) the variations of gaps between the band and wrist surface. This is a key point of our approach.

For measurement of the pronation angle change, the new sensing device is separated into two wrist parts. The wrist surface displacement, while changing the pronation angle, varies according to the distance from the elbow, which means that the pronation angle can be estimated by measuring the posture difference of the two wrist parts attached at different places of the wrist. The posture of each part is measured by an IMU installed on each part. Assuming the forearm as a rigid body and the forearm stops, the difference of the gravity direction measured by two acceleration sensors can be a clue to estimate the posture difference of two parts: the pronation angle. In contrast, if the forearm moves dynamically, then the posture difference can be estimated from the angular velocity sensors.

Approximately four steps are used for wrist contour measurements and Hand shape classification.

1. Wrist contour and IMU data are collected and transmitted from the sensing device to a PC via wireless communication.
2. The raw wrist contour data are converted to calibrated distance data using calibration data. IMU data are converted to the pronation angle.
3. The wrist contour distance data are converted to various statistics through data segmentation and feature extraction.
4. The hand shape is estimated by a classifier based on multiple statistics.

3. Wearable wrist contour sensing device

Figure 3 presents an overview of the developed device. The device consists of two parts: a control part and an end part. These parts are connected by a wire. The control part is fixed to the wrist by a fixing band. The end part is fixed by a measurement band. The wrist contour measurement and pronation angle estimation technologies are the core of the device.

![Figure 3. Wearable wrist contour sensing device.](image)

### Table 2. List of wrist contour measurement specifications.

<table>
<thead>
<tr>
<th>Properties</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measurement pitch</td>
<td>2.5 mm</td>
</tr>
<tr>
<td>Radial resolution</td>
<td>0.1 mm (range: ~3.5 mm)</td>
</tr>
<tr>
<td>Measurement area</td>
<td>Up to 185 mm</td>
</tr>
<tr>
<td>Measurement band width</td>
<td>25 mm</td>
</tr>
<tr>
<td>Sampling rate</td>
<td>20 Hz</td>
</tr>
</tbody>
</table>

3.1. Wrist contour measurement technology

Based on discussions related to human factors, specifications of wrist contour measurement are configured as Table 2 presents.

Two lines of a 75 distance sensor array are installed on the measurement band. The distance sensors are infrared photo-reflectors (NJL5901-AR1; New Japan Radio Co. Ltd.). They are installed at 2.5 mm pitch. Output characteristics of the photo-reflector are not linear to the distance from an object. Therefore, the voltage outputs of the photo-reflectors are converted to distance data by comparison with calibration data acquired using a previously developed calibration equipment.

To reduce the measurement band width, a sensor switching method using shift registers is adopted. The method can reduce the number of wires from sensors to the control part. All integrated circuit chips are so small that the measurement band is flexible. To avoid slippage of the measurement band, urethane sheets with 5 mm thickness are attached to both edges of the band. These urethane sheets also contribute as buffer cushions to prevent the measurement band from compressing excessively.

Implementation details of the wrist contour measurement technology are described also in our previous work [9].

3.2. Pronation angle estimation technology

Figure 4 presents the definition of the pronation angle used in this paper. Both the control part and the end part are equipped with IMUs. They are three-axis acceleration sensors (ADXL345) and three-axis angular velocity sensors (MPU-3050). Figure 5 shows positions where those IMUs are mounted and their coordinate systems. Figure 6 shows how the relative posture of the control part and the end part varies according to the pronation angle. The relative angle is estimated by comparing the output vectors of the acceleration sensors and the angular velocity sensors. Algorithm 1 shows the details of the procedure. First, the outputs for y-axis are ignored assuming the y-axes of sensors are placed parallel. Vector $w_i'$ is the output of the $x$- and $z$-axes of gyroscope $i$ ($i = 1, 2$). Vector $a_i'$ is the outputs of $x$- and $z$-axes of accelerometer $i$ ($i = 1, 2$). Then, the angles of gyroscope vectors and accelerometer vectors ($\theta_{yw}, \theta_{ya}$) are calculated. The relative angle of sensor units is the weighted sum of $\theta_{yw}$ and $\theta_{ya}$ (weights are calculated...
Algorithm 1 Estimate relative angle $\theta_y$

\[
\begin{align*}
    w_1' &= [w_{1x}, w_{1z}], w_2' &= [w_{2x}, w_{2z}] \\
    a_1' &= [a_{1x}, a_{1z}], a_2' &= [a_{2x}, a_{2z}] \\
    \theta_y &= \text{angle}(w_1', w_2') \\
    \theta_{ya} &= \text{angle}(a_1', a_2') \\
    n_w &= \text{norm}(w_1') + \text{norm}(w_2') \\
    n_a &= \text{norm}(a_1') + \text{norm}(a_2') \\

    \text{Require:} & \quad 0 \leq r_w, r_a \leq 1 \\
    r_w &= 1 - r_w \ast n_w \\
    r_a &= r_w \ast n_w + r_a \ast n_a \\
    \theta_y &= r_w \theta_y + r_a \theta_{ya} + (w_{2y} - w_{1y}) \Delta t
\end{align*}
\]

4. Wrist contour data collection and analyses

The wrist contour changes depending on the hand shape, device attaching condition, individuality, pronation angle, and so on. This section describes wrist contour data collection using the developed device and observation of data variations. In all, 19 women and men participated in this data acquisition process. Participants formed six hand shapes (Figure 7) with eight pronation angles (22.5° pitch). In each form, 10 samples were collected. By repeating the same procedure and re-attaching the device before each trial, six data-sets were acquired. Eventually, 54,720 samples were collected (= 19 participants × 6 hand shapes × 8 pronation angles × 10 samples × 6 sets). Figure 8 shows example data of two participants and six hand shapes where the pronation angle is fixed. The upper graph shows the wrist contour acquired from the distal (hand) side sensor array. In contrast, the lower graph represents data from the proximal (elbow) side sensor array. The horizontal axis is the sensor number. The number increases from the dorsal side to the radial side, palmar side, ulnar side, and dorsal side again. The vertical axis is the distance between the sensor and the wrist surface. As the figure shows, their values themselves are substantially different, but the following similarities are observed between the two participants.

- In the proximal (elbow) side wrist contour (lower graph) of ‘Thumbs up,’ left side values (#3–10) become larger.
- In the proximal (elbow) side wrist contour of ‘Fist,’ center values (#20–35) become larger.
- Values of ‘Index and middle’ are larger than those of ‘Open hand’ in almost all sensors. However, they become smaller on the left side (#3–10).

Figure 9 presents wrist contour data obtained while changing the pronation angle for a participant and a hand shape ‘Index.’ The wrist contour varies continuously depending on the pronation angle.

5. Hand shape classification experiment

5.1. Data forming, statistics conversion, and classifier

To recognize the hand shape from the wrist contour data, the following data forming process and statistics conversion were applied. Our process produces six full length data lines: two raw data lines from distal and proximal side sensor arrays, and four differential data lines. The four

---

Figure 4. Definition of pronation angle.

Figure 5. Axes of IMUs.

Figure 6. Relative displacement of two parts according to the pronation angle change.

Figure 7. Figure 6 (Figure 7) with eight pronation angles (22.5° pitch). In each form, 10 samples were collected. By repeating the same procedure and re-attaching the device before each trial, six data-sets were acquired. Eventually, 54,720 samples were collected (= 19 participants × 6 hand shapes × 8 pronation angles × 10 samples × 6 sets). Figure 8 shows example data of two participants and six hand shapes where the pronation angle is fixed. The upper graph shows the wrist contour acquired from the distal (hand) side sensor array. In contrast, the lower graph represents data from the proximal (elbow) side sensor array. The horizontal axis is the sensor number. The number increases from the dorsal side to the radial side, palmar side, ulnar side, and dorsal side again. The vertical axis is the distance between the sensor and the wrist surface. As the figure shows, their values themselves are substantially different, but the following similarities are observed between the two participants.

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- In the proximal (elbow) side wrist contour of ‘Fist,’ center values (#20–35) become larger.
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Figure 9 presents wrist contour data obtained while changing the pronation angle for a participant and a hand shape ‘Index.’ The wrist contour varies continuously depending on the pronation angle.
differential data lines are produced by taking the difference between two raw data lines and two calibration data, respectively. In addition to the full length data lines, three different segmented data lines are produced. These data lines are divided into two, three, or four segments at even intervals. This segmentation is expected to realize robust statistics conversion against slippage between the measurement band and the wrist. Eventually, 60 data lines are produced in our data forming process: 6 data lines × 10 (=1+2+3+4) segmentations.

In our previous work [9], we used statistics for classification such as the sum of distances and a histogram of distances. In addition to those statistics, distance center of gravity (\(\phi\)Gravity center in Equation (1)) and three low-
frequency elements ($\phi_i$ ($i = 1, 2, 3$)) of the Haar Wavelet Transform (Algorithm 2) [12] are used in this study, where $x_i$ ($i = 1, \ldots, n$) are data lines produced through the data forming process.

$$\phi_{\text{Gravity center}} = \frac{\sum_{i=1}^{n} x_i i}{\sum_{i=1}^{n} x_i} \quad (1)$$

The statistics become 39 dimensions: (1) sum of distances, (2) sum of differences, (3) maximum distance, (4) minimum distance, (5) maximum monotone increment value, (6) maximum monotone decrement value, (7) ratio of the former half sum to the latter half sum, (8–30) distance histograms (2, 3, 4, 6, and 8 bins), (31–35) histogram scores comparing with the one of Fist (2, 3, 4, 6, and 8 bins) [9], (36) distance center of gravity, and (37–39) three low-frequency elements of the Haar Wavelet Transform. Finally, 2,340 dimension statistics (=$60$ data lines $\times$ 39 statistics) were produced.

A multi-class support vector machine with a linear kernel [13] was used to classify the hand shapes based on the produced statistics.

### Algorithm 2 Haar wavelet transform

Require: $N = 2^T$

```
N = N
while n > 1 do
    n = n/2
    for i = 1 : n do
        $\phi_i = (x_{2i} + x_{2i+1})/2$
        $\phi_{i+n} = (x_{2i} - x_{2i+1})/2$
    end for
    for i = 1 : 2n do
        $x_i = \phi_i$
    end for
end while
```

### 5.2. Experimental configurations

Experimental configurations are as shown below.

- Target hand shapes: four classes (FI, TU, IN, and OH) or six classes (FI, TU, IN, OH, LI, and IM) in Figure 7.
- Training data: the evaluating participant’s own data or others’ data that exclude the evaluating participant data.
- Preliminary pronation estimation: with or without (W/O).

In the configuration with pronation estimation, experimental data are preliminary divided into eight groups based on the results of pronation angle estimation. In the configuration without the pronation estimation, all data including various pronation angles are used in both training and evaluation.

- Calibration hand shapes: fist and open hand.
- Pronation calibration poses (only for configuration with pronation estimation): Three poses (pronation angles are $0^\circ$, $90^\circ$, and $180^\circ$).

### 5.3. Experimental results

Figure 10 presents a summary of the experimental results. The classification performance is evaluated by classification rate. The classification rate is calculated as the number of correctly classified samples divided by the number of input samples. Experimental results show that the classification rate is about 90% in four classes and 80% in six classes irrespective of whether the preliminary pronation angle estimation is used or not. The 10% difference of classification rate in four and six classes indicates the need to optimize the number of target hand shapes based on the required accuracy. This phenomenon is almost identical to that described in a previous work [9].

Figure 11 shows the average classification rates of each participant when six hand shape classes are recognized, the training data include the evaluating participant data, and the classifier does not use the pronation estimation. The worst rate is 71.9%, and the best rate is 91.7% (The average is 79.8% as described in Figure 10). The ±10%...
Figure 12. Sum of differences values in various pronation angles and three different hand shapes. Raw data lines from proximal side sensor arrays. Left: second segment of three segments. Right: second segment of four segments.

Figure 13. Confusion matrix when pronation estimation is not used and the training data are the evaluating participant’s own data. The difference indicates both the diversity of the participants and the stability of the classification performance.

The difference between configurations with and without the pronation estimation is less than 0.5%. This result indicates two important possibilities: (1) the wrist contour has some features that depend on the hand shape but which do not depend on the pronation angle, or (2) the wrist contour potentially includes pronation angle variation information. As a clue of the first insight, Figure 12 shows the trend of a statistic; sum of differences. The sum of differences slightly changes depending on the pronation angle. However, the differences between hand shapes are more obvious compared with the change.

These insights suggest that hand shape can be recognized solely from the wrist contour without IMUs (or other equipment), even while changing the pronation angle.

Another important insight is that the classification rate worsens drastically if the training data exclude the evaluating participant data. Erroneous classification occurs between classes where the difference of finger poses is slight, as they are between FI and TU, LI and IN, and between IM and OH. These results indicate that the combination or sequence of hand shapes must be optimized when this device is used for a human–machine interface.

Figure 14. Confusion matrix when pronation estimation is not used and the training data are other data that exclude the evaluating participant’s data.

Figures 13 and 14 show details of the experimental results. The confusion matrices when the pronation estimation is not used and the training data are the evaluating participant’s own data or other data that exclude the evaluating participant data. Erroneous classification occurs between classes where the difference of finger poses is slight, as they are between FI and TU, LI and IN, and between IM and OH. These results indicate that the combination or sequence of hand shapes must be optimized when this device is used for a human–machine interface.

6. Conclusion

We proposed an approach to hand shape recognition based on wrist contour measurements. This paper especially addressed two assignments. The first was development of a new sensing device in which all elements were installed in the wrist-watch-type device. The second was development of a new hand shape classifier that can accept pronation angle changes. New wrist contour data-sets were collected using the developed wrist-watch-type device under the condition that the pronation angle varies. Analyses of the collected data reveal two facts: (1) the wrist...
contour raw data differ among different users, but similarities exist depending on the hand shapes. (2) The wrist contour varies continuously depending on the pronation angle variation.

We conducted hand shape classification experiments in which participants need not fix their pronation angle. The classification rate was about 90% in four hand shape classes and 80% in six classes. In addition, the experimental results reveal two important possibilities: (1) the wrist contour has some features that depend on the hand shape but which do not depend on the pronation angle, or (2) the wrist contour potentially includes pronation angle variation information. These results underscore the possibility that hand shape can be recognized solely from the wrist contour without IMUs (or other equipment) even while changing the pronation angle. As future work, it is necessary to improve the hand shape classification rate even when it is not possible to acquire training data of the user. To address this assignment, utilization methods of other users’ training data should be examined and evaluated.

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Rui Fukui received bachelor and master degrees from the University of Tokyo in 2002 and 2004, respectively. From 2004 to 2006, he was an engineer of Special Vehicle Designing Section, Mitsubishi Heavy Industries, Ltd. From 2008 to 2009, he was a Research Fellow (DC2) of Japan Society for the Promotion of Science (JSPS). In 2009, he received PhD (Information Science and Technology) from the University of Tokyo. From 2009 to 2013, he was a (Project) Assistant Professor of Department of Mechano-Informatics, the University of Tokyo. Since 2013, he has been with the Electrotechnical Laboratory (ETL) of the Ministry of Industrial Science and Technology. His research interests include machine intelligence, ubiquitous computing, and pervasive health. He is a member of the RSJ, ACM, IEEE, SICE, JSAE, JSAI, and JSME.

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