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## Immediately-Available Input Method Using One-Handed Motion in Arbitrary Postures

Moyuru Yamada<sup>a</sup>, Jiang Shan<sup>a</sup>, Katsushi Sakai<sup>a</sup>, Yuichi Murase<sup>a,\*</sup>, Keiju Okabayashi<sup>a</sup>

<sup>a</sup>*Human Centric Computing Laboratories, Fujitsu Laboratories Ltd., Atsugi, Kanagawa, Japan*

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### Abstract

This paper presents an input method, which enables the user to immediately interact with services using one-handed motion in arbitrary postures. This method is mainly targeted at workers who work with dirty hands or hold tools in their hands. To allow the workers to control applications as intended without handheld devices while they operate their hand work in various postures, we propose intentional segmentation, motion trajectory estimation of the wrist, and three types of inputs using wrist motions. The segmentation controller enables users to intentionally distinguish input motion from normal hand work by the wrist state without limiting the range of upper limb motion and immediately start performing the input motion. We estimate the motion trajectories of the wrist in the input segment using inertial sensors attached to the wrist, and recognize gestures from the trajectories without training data sets. The users can control various applications by three types of inputs: continuous inputs linked to the wrist motions, discrete inputs by gestures, and specific inputs generated from these. We also developed a wristwatch-like wearable device to evaluate the effectiveness of the proposed method. Through the two experimental evaluations, we showed the ease of learning the proposed method and achieved a mean recognition rate of 94.3% in various postures for six defined gestures.

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*Keywords:* Wearable input technologies; Hands-free interaction; Motion trajectory estimation

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## 1. INTRODUCTION

Recent progress in mobile computing has made it possible to provide support services in a timely fashion, which enables fieldwork to be more efficient with fewer errors or oversights, even when the workers are not experts. Although such services are currently available through handheld smart devices, some work settings are not amenable to the use of such devices because workers often wear gloves, work with dirty hands, or hold tools in their hands. In our supposed applications, such as building maintenance and car inspection, the workers conduct their tasks in various postures at each work area they move to. Although their input motions for obtaining instructions or reporting task completions are infrequent in the entire workflow, the workflow should be interrupted as little as possible. Therefore, the workers need an immediately-available input method that enables them to seamlessly interact with the services and perform normal work without holding the devices.

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\* Corresponding author. Tel.: +81-46-250-8218 ; fax: +81-46-250-8841.

*E-mail address:* [murase.yuuichi@jp.fujitsu.com](mailto:murase.yuuichi@jp.fujitsu.com)



Fig. 1. An immediately-available input method that enables workers to interact with support services while performing their hand work with a tool.

Many researchers have studied wearable input devices using the voice, finger, and wrist motions. Voice input is commonly used for head mounted displays (HMDs), such as Google Glass<sup>1</sup>. However, voice input is generally sensitive to surrounding noise, and security issues arise with its use in business. Some studies have investigated finger shape recognition by capacitance sensing<sup>2</sup>, IR cameras<sup>3</sup>, or forearm electromyography<sup>4</sup>. Finger ring devices have also been investigated to enable subtle interactions<sup>5,6</sup>. Although these approaches can be performed without arm motion, their use is limited in some work settings where workers hold tools in their hands or work with dirty hands.

We present an immediately-available input method using single-wrist motion. This method enables users to immediately interact with the services as intended by using a wrist device while performing their hand work (Fig. 1). The key features of the method are intentional segmentation, trajectory estimation, and three types of inputs to control applications. The segmentation method allows users to intentionally distinguish the input motion from normal hand work by only a single-wrist state that is not common in everyday tasks. In this intended input segment, motion trajectories of the wrist in arbitrary postures are estimated using the inertial sensors in the wrist device. Gestures can be recognized based on the trajectories without training data sets. We also designed an interface that offers three types of inputs: continuous inputs linked to the wrist motion, discrete inputs by gestures, and specific inputs generated from these, to control various applications. We focus on the estimation of intended input motions in arbitrary postures rather than the recognition of specific discrete gestures. Our main contributions can be summarized as follows:

- Intentional segmentation, by using only a single-wrist state that is not common in everyday tasks.
- Trajectory estimation of the wrist motion in arbitrary postures for application control and gesture recognition.
- Three type of inputs using wrist motions to control various applications.

The remainder of this paper is organized as follows: we first present related work, then a description of our approach. Next, we give details of our system design and implementation. We present the wrist device, which is a wristwatch-like wearable device developed by us. We then show two experimental evaluation results. Finally, we discuss the limitations and future plans for our study and then reach our conclusions.

## 2. RELATED WORK

Many studies have been conducted on wearable devices to interact with services using hand and wrist motions. The motions are generally sensed by using cameras or inertial sensors. The vision-based approaches make it possible to augment interaction with the physical world<sup>7,8,9</sup>. Unfortunately, this approach typically requires the users to hold their hands in front of the camera, which is an unreasonable constraint for workers who operate with their hands in various positions. To resolve this problem, we attached inertial sensors to the wrist to sense its motions. Many studies have investigated gesture recognition by using the inertial sensors<sup>10,11,12</sup>. However, these methods spot defined gesture patterns, regardless of whether the workers intend to input to the services or are merely moving their working hands. A simple method for allowing intentional segmentation is to have the user press a button only when the user wants to input the gesture<sup>13,14</sup>. Although this is a simple and clear method of control, the user is required to hold the device. For a gesture input using a wrist watch, Lee and Jungsoo controlled segmentation by tilting the wrist up<sup>15,16</sup>. Although our approach is based on this segmentation method, it requires only a single-wrist motion, whereas the previous studies required both hands to input gestures. This difference is significant because workers can often use only one hand. Shahram et al. used foot gestures to activate or deactivate the hand gestures during a surgery<sup>17</sup>. However, this approach is not reasonable when the user walks around.

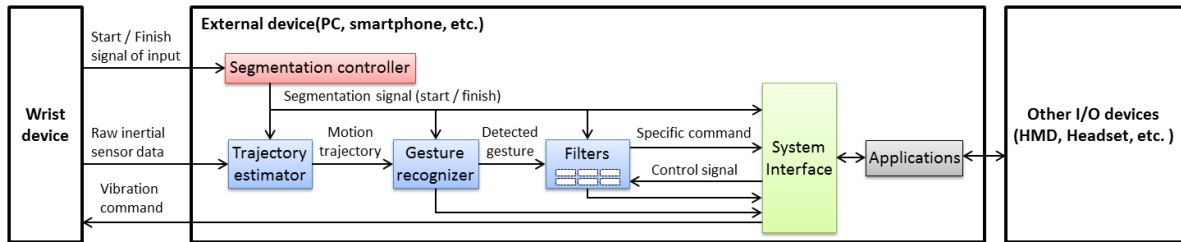


Fig. 2. System structure. (e.g. if users carry a smart phone in a pocket and wear the wrist device and a headset, they can seamlessly perform normal activities while interacting with the voice support application using the wrist motions.)

### 3. METHOD

We describe our approach for achieving the immediately-available input method using single-wrist motion. This input method mainly targets workers engaged in factory or building maintenance and other field work. Although their work flow differs, typical applications can be controlled by three input types: continuous inputs linked to wrist motion such as mouse cursors, discrete gesture inputs such as mouse clicks, and specific inputs generated from these two inputs such as double-clicks and mouse gestures. These inputs should be performed in arbitrary wrist postures to interrupt as little as possible because the workers operate their hand work in various positions. To enable the user to effortlessly control the application as intended in arbitrary postures, we estimated the trajectories of the input motions in coordinates based on human kinematics property from inertial sensor data. The motion trajectories are used not only to be the continuous inputs but also to recognize the gestures. The accuracy of gesture recognition using machine learning typically depends on the training data<sup>18</sup>. Our gesture recognition adopts a rule-based approach because the requirement for large training data sets for an individual worker is not reasonable in practice. In addition, the approach enables the applications to feed back the progress of gesture recognition to the user, and this feedback ensures that the user is aware of unintended input, enabling cancellation or alteration of the wrist motion. Since a necessary and sufficient number of simple gestures are needed for application control, we defined simple six gestures described in the section 4.4 in consideration of our targets.

The wrist motions should be regarded as input motions only when the user intends to perform an input. To intentionally distinguish input motion from non-input motion without using the hands, the motion or state of an upper limb should be used. However, if a preliminary gesture or posture limitation of the upper limb is needed, the input motion cannot be performed immediately. To solve these problems, we leverage the uncommon wrist state of the upper limb used for the input motion. The two main approaches to switching the motion input state include the activated or deactivated state where the wrist motions are regarded as an input motion or non-input motion. The first approach switches the motion input state when the wrist reaches the uncommon state. Although this approach does not require the user to keep the wrist state during the input motions, the user must remember the current motion input state. The second approach regards the wrist motions as the input motions only when the wrist is in the uncommon state. We chose the second approach, which enables the user to perceive whether the motion is activated with eyes-free. In the next section, we design and implement a system based on the proposed approaches as mentioned above.

## 4. SYSTEM DESIGN

### 4.1. System Overview

We designed and implemented our system in interaction with various applications using the proposed input method. This system consists of three types of devices: the wrist device, external devices, and other I/O devices, as shown in Fig. 2. The wrist device is a wearable device attached to the wrist that wirelessly transmits raw inertial data, and start and finish signals of the input motion to an external device. The external device controls the applications on the basis of the received input from the wrist device and also communicates with other devices such as HMD and a headset. For example, if a user carries a smartphone in a pocket and wears the wrist device and a headset, he/she can seamlessly perform normal activities while interacting with the voice support application by using wrist motions.

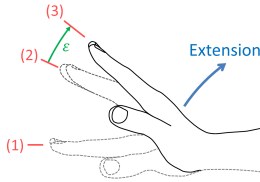


Fig. 3. Uncommon range  $\epsilon$  of wrist joint. (1) Normal, (2) relaxed, and (3) intentionally tilted states.

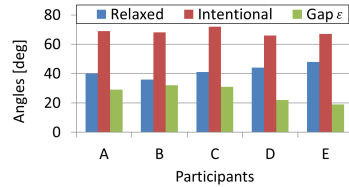


Fig. 4. Gap between relaxed and intentional wrist angles. (Five participants)

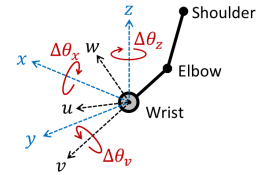


Fig. 5. Wrist motion coordinates  $x$ - $y$ - $z$ . Gyro data in coordinates  $u$ - $v$ - $w$  is transformed to the data in these coordinates.

Three types of inputs to control the applications are generated in the external device as follows. First, the segmentation controller starts or finishes the process of the trajectory estimator, gesture recognizer, and filter when the start or finish signals are received. The trajectory estimator estimates continuous trajectories of wrist motion from the raw inertial sensor data. Then, based on the estimated motion trajectories, simple gestures are continuously recognized in real time, and some gestures may be detected in a segment. In some cases, common filters are used to generate specific commands from the motion trajectories and gestures. The system interface offers an application interface (API) that enables application control through wrist motion. The applications can catch the events such as start or finish of input, wrist movement, and gesture detection through API. The API also includes notifications for the user. If a notification command is sent, the wrist device vibrates its motor once in several vibration patterns. These vibrations notify the user that it has detected the gesture or an alert from the application.

#### 4.2. Segmentation Controller

The segmentation controller controls the segmentation by the start and finish signals from the wrist device. These signals are transmitted on the basis of the wrist state of the upper limb used for motion input. The wrist joint does not limit the range of upper limb motion and hand posture because it is at the end of the upper limb that can be modeled as a serial link with seven degrees of freedom (DOF)<sup>19,20</sup> with one redundant DOF. To achieve intentional segmentation control by the user, we leverage the uncommon wrist state. The wrist joint has one DOF and is generally used up to  $35^\circ$  in extension in daily activities, while it can be intentionally rotated up to approximately  $70^\circ$ <sup>21</sup>. To investigate the wrist rotation angle, five participants (age twenties to forties) were instructed to keep the forearm at the upright position and then to relax the wrist and hand ((2) in Fig. 3) or to intentionally rotate the wrist in an extension ((3) in Fig. 3). Each rotation angle was measured by a potentiometer attached to the wrist. The results show a gap  $\epsilon$  of more than approximately  $20^\circ$  between the intentional rotation angle and the relaxed angle (Fig. 4). Therefore, we activate the motion inputs when the wrist is in this intentional angle range. Because the processes of the trajectory estimation and gesture recognition are executed only when the motion input is activated intentionally, false detections can be prevented.

#### 4.3. Trajectory Estimator

The trajectory estimator estimates the wrist motion in arbitrary postures on the basis of the raw inertial sensor data. We used a three-axis accelerometer and gyroscope. Because the axes of these inertial sensors are fixed to the wrist, the raw sensor data in each axis is affected by the wrist postures. Therefore, the direction of translational motion in coordinates fixed to the torso is difficult to estimate in arbitrary postures from only these inertial sensors, because an initial absolute orientation cannot be obtained in general. To resolve these problems, we defined wrist motion coordinates that enable description of the wrist motion regardless of postures, as shown in Fig. 5.

In this coordinate system, orthogonal coordinates  $u$ - $v$ - $w$  are fixed to the inertial sensors attached to the wrist. Axis  $v$  is parallel to the forearm, and axis  $w$  is normal to the top side of the hand. The raw acceleration and gyro data are obtained in these coordinates. The coordinates  $x$ - $y$ - $z$  are the proposed wrist motion coordinates. The  $z$  axis is parallel to the gravity vector. The  $x$  axis is at right angles to the  $z$  axis and  $v$  axis. The axes  $x$ ,  $y$ , and  $z$  are at right angles to each other.  $\Delta\theta_u$ ,  $\Delta\theta_v$ ,  $\Delta\theta_w$ ,  $\Delta\theta_x$ ,  $\Delta\theta_y$ , and  $\Delta\theta_z$  are rotation angles of the  $u$ ,  $v$ ,  $w$ ,  $x$ ,  $y$ , and  $z$  axes from an initial posture, respectively. The proposed coordinates are based on the fact that the natural wrist motion trajectory is

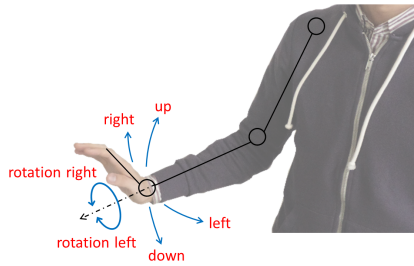


Fig. 6. Six defined gestures (up, down, left, right, rotation left, rotation right). Each gestures is detected only when the user tilts the wrist up in an uncommon range.

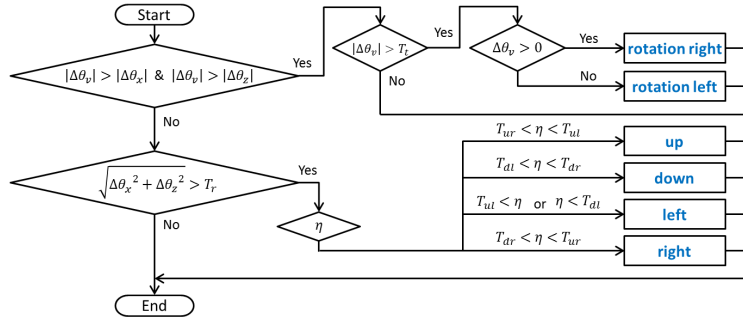


Fig. 7. Flow chart of gesture recognition.  $\eta$  is calculated by equation (4). Gestures can be continuously recognized in real time, and some gestures may be detected in a segment.

curved but linear<sup>22,23</sup>, because the human body is modeled as a serial link in which each joint rotation involves wrist posture change. We estimated the wrist motion through the following steps. First, the initial posture angles in the  $x$ - $y$ - $z$  coordinates  $\theta_{x0}$ ,  $\theta_{y0}$ ,  $\theta_{z0}$  are calculated by equation (1) on the basis of the acceleration data provided when the start signal is received.

$$\theta_{x0} = \sin^{-1} \frac{a_v}{G}, \theta_{y0} = \tan^{-1} \frac{a_u}{a_w}, \theta_{z0} = 0, \tag{1}$$

where the  $G$  is gravity acceleration,  $a_u$ ,  $a_v$ , and  $a_w$  are accelerations of the  $u$ ,  $v$ , and  $w$  axes, respectively. Then, angular velocities  $\omega_x$ ,  $\omega_y$ , and  $\omega_z$  in the  $x$ - $y$ - $z$  coordinates are calculated by

$$\begin{pmatrix} \omega_x & \omega_y & \omega_z \end{pmatrix}^T = R \begin{pmatrix} \omega_u & \omega_v & \omega_w \end{pmatrix}^T, \tag{2}$$

where a rotation matrix  $R$  that represents the transformation of angular velocities  $\omega_u$ ,  $\omega_v$ , and  $\omega_w$  in the  $u$ - $v$ - $w$  coordinates into  $\omega_x$ ,  $\omega_y$ , and  $\omega_z$ . This rotation matrix is initialized using the initial posture angles and updated on the basis of each reception of gyro data. Finally, the rotation angles of the wrist  $\Delta\theta_x$ ,  $\Delta\theta_y$ , and  $\Delta\theta_z$  are obtained by integrating the angular velocities  $\omega_x$ ,  $\omega_y$ , and  $\omega_z$ , respectively. Actually,  $\Delta\theta_x$ ,  $\Delta\theta_z$ , and  $\Delta\theta_v$  express the wrist motion in the directions of up-and-down, right-and-left, and twist. We leverage the trajectories of these rotation angles as continuous inputs and to recognize the gestures. Because the motion trajectories depend mainly on the single integral of the gyro data and are reset at the start of input, accumulation of errors caused by the sensor noises can be safely ignored. Singular postures include in which the hand is held directly overhead or underneath. At those postures, the initial postures cannot be obtained properly because the  $y$  axis is parallel to the gravity vector. However, when the wrist is naturally in these postures, we consider the  $\Delta\theta_u$ ,  $\Delta\theta_v$ , and  $\Delta\theta_w$  to correspond to the wrist motion  $\Delta\theta_x$ ,  $\Delta\theta_y$ , and  $\Delta\theta_z$ .

#### 4.4. Gesture Recognizer

The gesture recognizer recognizes six defined gestures on the basis of the estimated rotation angles. The defined gestures include up, down, left, right, rotation left, and rotation right as shown in Fig. 6. These gestures are simple motions and can be performed in arbitrary postures. The defined gestures are divided into two gesture sets of translation gestures (up, down, left, and right) and rotation gestures (rotation left and rotation right). Gesture recognition begins when the norm of the angular velocities  $\omega_x$ ,  $\omega_y$ , and  $\omega_z$  is smaller than the threshold  $T_{st}$  or when the segment is finished by tilting down the wrist. Figure 7 shows a flow chart of gesture recognition. If equation (3) is satisfied, input motion is regarded as a rotation gesture candidate, otherwise, it is recognized as a translation gesture candidate.

$$|\Delta\theta_v| > |\Delta\theta_x| \quad \text{and} \quad |\Delta\theta_v| > |\Delta\theta_z|. \tag{3}$$

The rotation gestures can be detected when the amplitude of the rotation angle  $\Delta\theta_v$  is greater than the threshold  $T_r$  and is distinguished on the basis of only the sign of  $\Delta\theta_v$ . If the sign is positive, the gesture is recognized as rotation right, otherwise, it is regarded as rotation left. The translation gestures can be detected if the norm of  $\Delta\theta_x$  and  $\Delta\theta_z$  is greater than the threshold  $T_r$ . Then, each rotation gesture is recognized on the basis of the index  $\eta$  calculated by equation (4).

$$\eta = \tan^{-1} \frac{\Delta\theta_x}{\Delta\theta_z}. \tag{4}$$

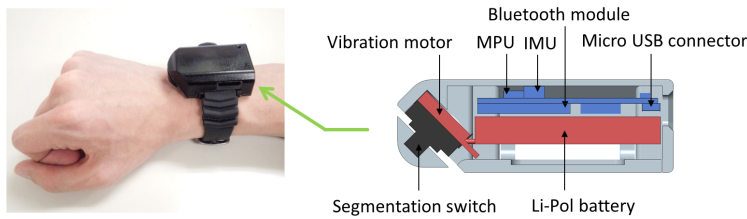


Fig. 8. Photograph and main components of proposed wrist device.

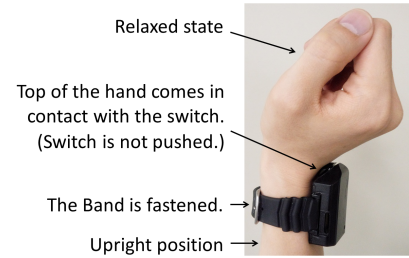


Fig. 9. Attachment position of the wrist device.

Each direction threshold  $T_{ur}$ ,  $T_{dr}$ ,  $T_{ul}$ , and  $T_{dl}$  is determined through preliminary experimentation.

#### 4.5. Filter

Filters generate specific inputs from the estimated motion trajectories and detected gestures. For example, input such as a double-clicks can be achieved on the basis of the timestamp of the detected gestures, and other inputs such as a mouse gesture can also be recognized from the motion trajectories. In addition, the filters can eliminate unnecessary gestures from a sequence of detected gestures and generate only specific gestures based on its order and timestamp. These specific gestures are useful for the application because it needs different inputs depending on its state and usage. For example, some confirmation dialogs simply requires entering YES or NO, whereas eight gestures might be needed to control a different screen.

## 5. PROTOTYPE HARDWARE

To demonstrate the proposed method, we developed a wrist device, which is a wearable device worn like a wrist-watch, as shown in Fig. 8. The wrist device has a segmentation switch to enable the user to intentionally control the segmentation. When this switch is pushed or released, the micro processing unit (MPU) MSP430 detects a switch status change and transmits the start or finish signal to an external device through Bluetooth. The switch is pushed by the top of the user's hand and provides the user "click" sensation. The tactile feedback enables the user to perceive whether the motion input is activated with eyes-free. To prevent false detections of input motions, the user adjusts the attachment position of the wrist device so that the switch is pushed only when the user tilts the wrist until its extension angle reaches the uncommon range. Figure 9 shows an adequate attachment position, where the top of the hand comes in contact with but does not push the switch when the user keeps the forearm at the upright position and then relaxes the wrist. The belt of the wrist device is fastened to prevent the device from sliding down. Although relaxed wrist angle differs from individual to individual, this setup is simple and efficient. The wrist device also has an inertial measurement unit (IMU) MPU-9150. The accelerometer and gyro data of the IMU are transmitted only while the switch is being pushed. This mechanism reduces power consumption and improves operation time while being powered by an internal battery. The battery is an Li-Pol 400 mAh, and a 3.7V. Micro USB connector is used to recharge the battery. A vibration motor notifies the user of gesture detection or an alert from the application by its vibration for 100ms when a command is received from the external device.

## 6. EVALUATION

We evaluated the proposed input method through two experiments in which each of the gesture recognition parameters were determined by preliminary experimentation with several subjects dominated by the authors as follows:  $T_{st}$ ,  $T_t$ ,  $T_r$ ,  $T_{ur}$ ,  $T_{dr}$ ,  $T_{ul}$ , and  $T_{dl}$  are 0.55 [rad/s], 15.0, 10.0, 64.0, -30.0, 120.0, -135.0 [deg]. Although in the two experiments, the users keep wearing the wrist device and can input gestures at any time, there are no false detections of unintended input. We show three indices to evaluate the proposed method. The detection rate is the ratio of detected gestures to the motions intended to input the gesture; the accuracy rate is the percentage of correct gestures deduced from those detected; and the recognition rate equals the detection rate multiplied by the accuracy rate.

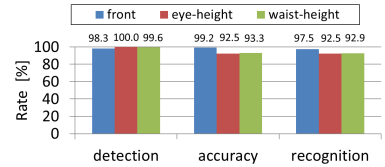
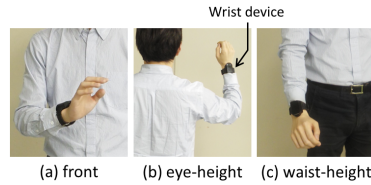
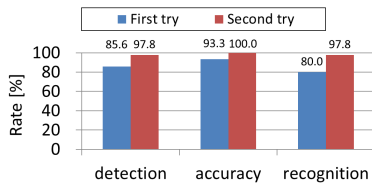


Fig. 10. Gesture recognition results before and Fig. 11. Three postures used for performing gesture after training (First try: before training; second try: after training). All participants were well trained for only posture (a).

Fig. 12. Gesture recognition results for three postures. (a) Their hands were in front of their chests or at the sides of the body at (b) eye-height and (c) waist-height.

We first investigated the intuitiveness and ease of learning the proposed method. In this investigation, we asked four participants from other research groups in our lab to perform six gestures 60 times (10 times for each gesture). After only a brief oral introduction of the six gestures and how to input them, we showed the target gestures randomly on a screen in front of the participant, who sat on a chair and performed the target gesture from natural hand positions. Although we did not impose hand position constraints on the participants, they positioned their hands in front of their chests in most cases. The target gesture proceeded to next one if the finish event of the segmentation was received from the wrist device. To eliminate the learning effect, the gesture recognition results were not shown to the participants and notifications by vibration of the wrist device were also disabled. After the first try, the participants were trained for several minutes on how to perform the gestures, and then second and subsequent investigations were conducted under the same conditions (6 gestures × 10 times × 2 conditions × 4 participants = 480 trials in total).

Figure 10 summarizes the results of the above experiment for usage effort. In the first try, the detection rate is more than 12% lower than in the second, which is 97.8%, because the user motions were initially too short. Furthermore, we determined that although the participants attempted to perform continuous inputs, the gesture of rotation left was difficult to input at the specific posture where the previous gesture finished. This problem is caused by the range of forearm pronation, which is approximately 90 degrees. It is difficult to rotate the forearm in a pronation direction with the palm facing downward. In the second try, the participants learned how far the wrist should be moved to input the gesture in the training. We obtained a high recognition rate of 97.8% without using the training data sets by giving the users just a short training session.

We then evaluated the accuracy of gesture recognition at three different postures to demonstrate that the proposed input method can be used for arbitrary postures. The other four participants were asked to perform each gesture at three different specific postures such that (a) their hands were in front of their chests or at the sides of the body at (b) eye-height and (c) waist-height, as shown in Fig. 11. All participants were well trained for only posture (a). The other experimental conditions were the same as in the previous experiment (6 gestures × 10 times × 3 postures × 4 participants = 720 trials in total).

The experimental results on various input postures are summarized in Fig. 12. In the case in which the hands were in front of the chest (a), each rate was almost the same as that in the second attempt in the previous experiment when the participants had only short training. This result indicates that the users can quickly learn the proposed method. The recognition rates at postures (b) and (c) were more than 92%, although the users were not trained for those postures. We obtained a mean recognition rate of more than 94.3% in various postures without using training data sets because the other postures were in the range of postures (b) and (c) and the aforementioned rate was best at position (a). The reductions in the accuracy rate in postures (b) and (c) were caused by changes in optimal direction thresholds, which were determined in posture (a).

## 7. DISCUSSION & FUTURE WORK

The segmentation switch of the wrist device was not pushed in most situations, although we conducted work throughout the day while wearing the wrist device. In addition, we can immediately perceive when the switch is pushed. However, we should investigate the fatigue involved using the uncommon state of the wrist and performance of the gesture recognition for a large number of participants. We will also improve our wrist device, especially its size, belt, and detection mechanism of wrist tilting to fit in actual workplaces.

## 8. CONCLUSION

We present an immediately-available input method using single-wrist motion, which enables the workers to immediately interact with the support services while conducting their hand work. The proposed method prevents false input detection by activating the wrist motion as the input only when the user is intentionally tilting the wrist up in the uncommon range. To enable the user to effortlessly perform the input as intended in arbitrary postures, we estimated the trajectories of the wrist motions from inertial sensor data and recognized six simple gestures based on the trajectories. The users can control the various applications by performing continuous wrist motions, discrete gestures, and specific inputs generated from them. We developed a wristwatch-like wearable device and demonstrated high accuracy gesture recognition in arbitrary postures and the ease of learning the proposed method.

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