Behind The Palm: Hand Gesture Recognition through Measuring Skin Deformation on Back of Hand by using Optical Sensors

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Abstract: We propose a system consisting of a wearable device equipped with photo-reflective sensors arranged in an array. Hand gestures are recognized by measuring the skin deformation of the back of the hand. Since the muscles and bones on the back of the hand are linked to the fingers, finger movement can be clearly observed. Skin deformation is measured using several photo-reflective sensors. Skin deformation can be determined by measuring the distance between the device and skin with these sensors. The system estimates hand gestures with a support vector machine using the sensor data. Since this system simultaneously records the hand shape using Leap Motion in the learning phase, a user can freely register gestures. The system further displays a reconstructed digital hand as a gesture-recognition result.

Keywords: Hand Gesture; Skin Deformation; Photo-Reflective Sensor.

1. INTRODUCTION

Methods for hand gesture recognition have been extensively studied. There are two typical methods: camera-based and glove-type. The camera-based method enables hand gesture recognition without limiting user movement because there is no need to wear a device [6][17]. However, there are restrictions regarding the place of use since cameras need to be installed and this method often has occlusion problems. The glove-type method can recognize hand gestures without occlusion [23], but the glove may limit hand movement.

In contrast with these two methods that measure the hand itself, there are methods that indirectly measure hand gestures. There have been many proposals for devices that are worn on the fingers [10][16], those that wrap around the wrist [2][4][5], and those that wrap around the forearm [11][24]. These devices do not limit a user's movement and are robust against occlusion. However, they cannot recognize various gestures, and their position must be adjusted depending on the user.

In this study, we focused on the back of the hand. Since the muscles and bones on the back of the hand are linked to the fingers, finger movements can be clearly observed. This position is less affected by the wearing of clothing compared to a device attached to the wrist or forearm.

Therefore, we propose a system that consists of a recognition method for detecting hand gestures through measuring the skin deformation on the back of the hand using photo-reflective sensors (Fig. 1). The system also consists of a wearable device we developed that has several photo-reflective sensors arranged in an array. These sensors enable the measurement of the distance of an object by emitting infrared light and measuring the intensity of the reflected light. Using the sensor data, gestures are identified using a support vector machine (SVM). Since this system simultaneously records the hand shape using camera based hand tracking device which is Leap Motion in the learning phase, the user can freely register gestures. The system further displays a reconstructed digital hand as a gesture-recognition result. There is a device for measuring the back of the hand using strain gauges [7], but our method is more durable and easier to equip.

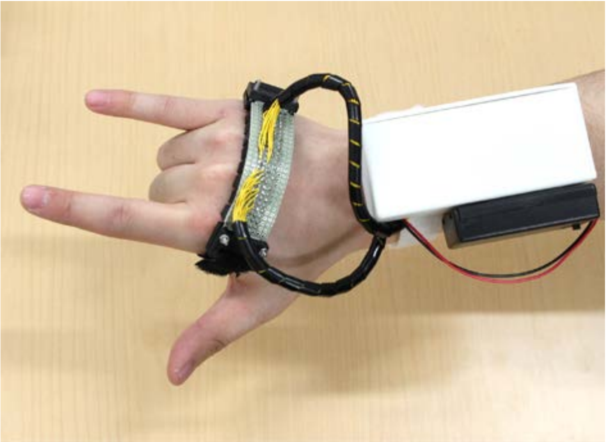

Fig.1 Prototyped device can capture user's hand gestures

2. RELATED WORK

2.1 Hand Gesture Recognition by Wearable Sensors

Sensors that measure hand movement by placing sensors on the whole hand are commercially available and are being used in various situations [23]. However, this may sometimes restrict natural hand movement.

There have been attempts to simply identify human gestures by reducing the mounting area and location of the device. Researchers have proposed a method of gesture recognition by using sensors worn on only a finger. iRing is a ring-shaped device with a light sensor mounted around it, with which it is possible to measure a user's finger-bending motion [16]. Liwei et al.

identified hand gestures using a camera equipped with a fisheye lens on a ring [1]. In addition, Mascaro et al. proposed a method of measuring the bending motion of fingers by attaching a photo sensor on a human fingernail and measuring color changes according to blood flow when bending a finger [10].

Many methods have been proposed for recognizing gestures with free hands by attaching devices to parts of the hand other than the fingers. In particular, many researchers have proposed devices that can recognize gestures by being wrapped around the wrist. Fukui et al. proposed a method of measuring wrist-shape deformation using photo-reflective sensors placed inside a wristband [4]. Dementyev et al. developed a sensor device with multiple pressure sensors inside a band. This device can measure the pressure distribution when a user performs hand gestures and recognizes them through machine learning [2]. GestureWrist uses capacitive sensors to recognize a small set of gestures [19]. WristWhirl is a wrist-band-type device that can recognize dynamic hand gestures using multiple piezo sensors attached around the band [5].

There are several methods for identifying gestures by attaching devices to a user's forearm. The Myo armband [11] uses electromyography to recognize hand gestures by measuring the movement of muscles of the forearm that are relevant to moving hand and fingers. Zhang et al. proposed a method of estimating the bone position of the hand and fingers by using tomography [24]. However, these methods have limitations regarding the number of available gestures.

2.2 Motion Recognition Using Photo-Reflective Sensors

Photo-reflective sensors are used in various situations [21][22]. There are various approaches to estimate body motion by measuring the deformation of the human skin with photo-reflective sensors. AffectiveWear is an eyewear device that can recognize human facial expression by attaching multiple photo sensors to the glass frames [9]. Nakamura et al. proposed a device with one photo-reflective sensor, which intuitively and seamlessly controls augmented reality information using the natural movement of eyebrows when users try to focus and stare at something [12]. Makino et al. proposed a sensing method of skin deformation on the forearm using photo-reflective sensors [8]. Ogata et al. applied the [8] system to a user interface [14][15], and Nakatsuma et al. developed a sensor system that can track finger motion on the back of the hand using photo sensors and is used as an input interface [13]. Our research aim was to measure the deformation of the skin of the back of the hand using photo-reflective sensors and identify hand gestures.

3. BEHIND THE PALM

3.1 Principle

When a human moves his/her fingers, the back of the hand is deformed. Finger movement is linked with the bones and muscles of the back of the hand (Fig. 2).

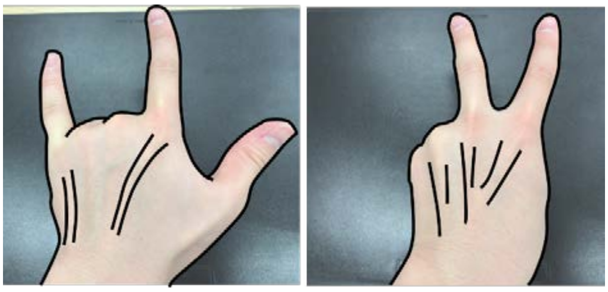

Fig.2 Deformation of back of hand by making gestures

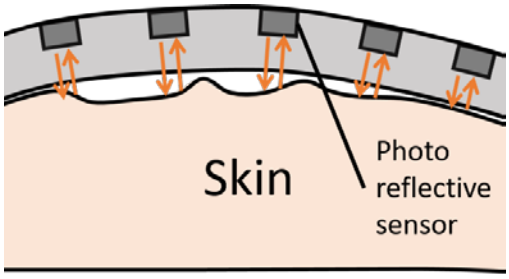

Fig. 3 Measurement principle

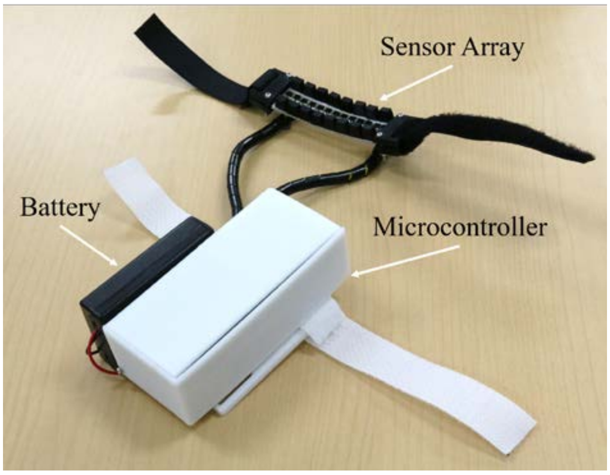

Fig. 4 Hardware device

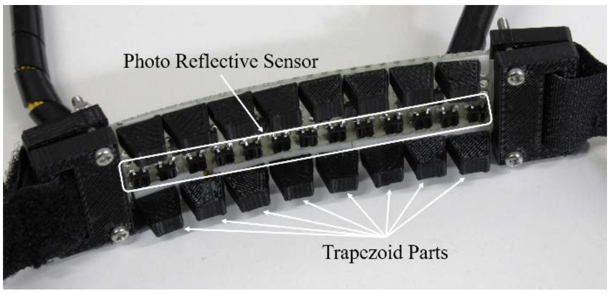

Fig. 5 Sensor array

Based on this human mechanism, our system detects skin deformation on the back of the hand by using photo-reflective sensors, which are combinations of an infrared LEDs and phototransistors (Fig. 3). A photo-reflective sensor can simplify the circuit configuration and does not require amplification. This type of sensor is generally used for measuring the

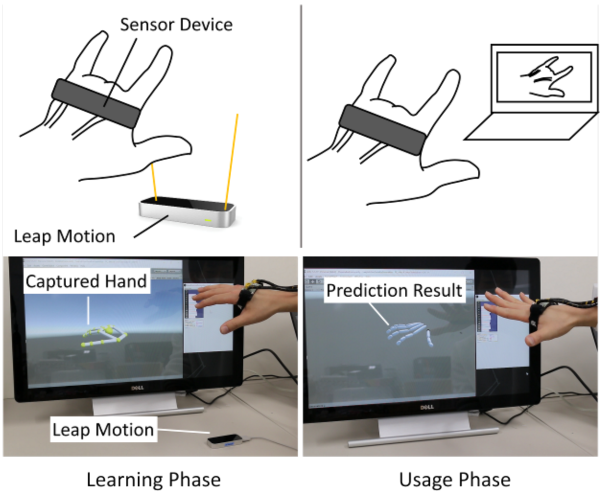

Fig. 6 Difference between learning and usage phases

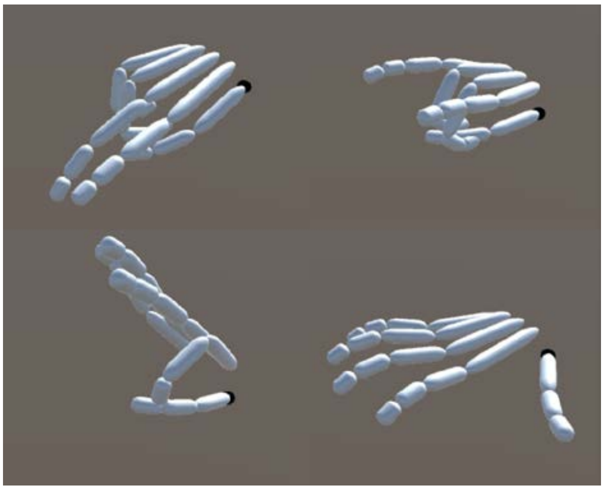

Fig. 7 Examples of reconstructed digital hands

distance between itself and an object. Our wearable device is equipped with several such sensors in an array (Fig. 4). Our device was designed to have a gap between the sensors and the surface of the skin when wearing it for measuring skin deformation.

3.2 Hardware

We placed 13 photo-reflective sensors in a straight array at 5.1-mm intervals (Fig. 4). Our device contains trapezoid components to make a gap between the sensors and skin (Fig. 5). These components enable the device to follow the deformation on the back of the hand even if the back of the hand is curved. Our device can be attached to and detached from a user's hand using Velcro tape. Therefore, the user does not need to use special tools when wearing it.

We used the optical sensors SG-105 manufactured by Kodenshi Co., Ltd. The optical sensors are connected to a microcontroller (Arduino Pro Mini, 3.3 V), and data are transmitted to a PC (Intel Core i7-4770 processor, 8-GB memory) through XBee which is wireless module. The device also has AAA batteries for driving the photo-reflective sensors, microcontroller, and XBee. Therefore, we can use the system without having to extend the wiring to the outside.

3.3 Recognition

Our system recognizes gestures using the optical sensors' data. To detect hand gestures, we use an SVM, which is a supervised machine learning technique. The SMV for processing (PSVM) library is used for implementation [18].

We first prepare a dataset of hand gestures. The user wears the device and accumulates the learning data by recording the sensor data when making hand gestures. At the same time, the system simultaneously measures the shape of the hand gesture using Leap Motion (Fig 6 left). A unique label is attached to the data of a 3D hand shape captured by Leap Motion. After that, the class of machine learning and label of 3D hand gesture are associated. This allows the user to register gestures that he/she wants to use. After learning, the system can detect hand gestures and display a 3D hand model on the PC screen (Fig. 6 right). We refer to the study by Rendl et al. for the method of correlating the shape-deformation data of the target measured using an external camera and the learning data of the sensor [20]. Figure 7 shows examples of reconstructed digital hands.

4. APPLICATIONS

We developed a hand-gesture-based text input system (Fig. 8) as an example application. There is a hand gesture that expresses each letter of the alphabet [3].

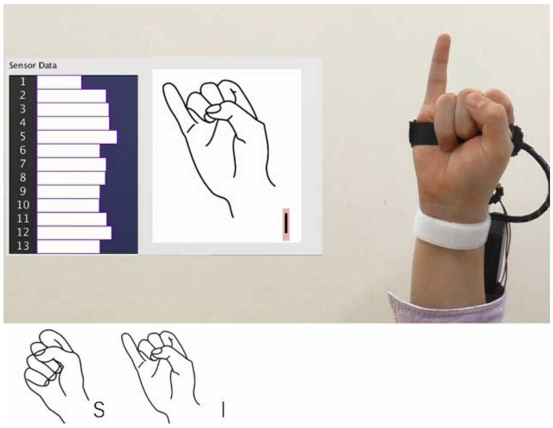

Fig. 8 Example application of text input for blind people

Fig. 9 Example application of input interface for virtual reality

Fig. 10 Prepared hand-gesture set in our experiment

Since our sensor device can recognize various gestures, it is possible to input text. Thus, it can be used as an input interface for blind people.

Our system can also be used as an input interface to capture human body movements in a virtual reality (VR) space (Fig. 9). Although there are camera-based systems, such as Leap Motion, there are problems of occlusion and recognition that they cannot detect when the distance between the hand and camera increases. However, these systems have great potential because they can be easily attached to and detached from a user's hand and allow various hand gestures to be used.

5. EVALUATION

We conducted a user study to investigate the recognition accuracy of hand gestures using our system. The hand gestures performed in the study are shown in Fig. 10. We prepared 20 gestures. These 20 gestures were designed based on the study by Lin et al. [7]. We found that our system can recognize many gestures more than the previous research through preliminary experiment, so we added more gestures. Before the user study, we gave instructions to the participants regarding each gesture. The participants were instructed to sit on a chair and make one hand gesture at a time from gestures 1 to 20. While collecting the data, the participants were instructed to maintain the hand gesture until instructed. We collected 6000 data per person (300 data * 20 hand gestures). The participants were 3 men and 1 woman in their 20s. The dataset collected from each participant was applied to three-fold cross validation. The training dataset per participant was applied to an SVM with a linear kernel.

The average recognition accuracy was 99.5% and standard deviation was 0.90%. This result indicates that

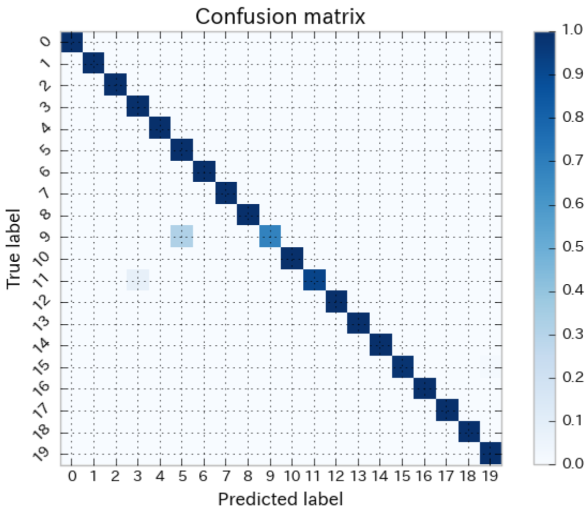

Fig. 11 Confusion matrix of 20-gesture experiment of one participant with whom device accuracy was lower than others

our system was basically able to recognize hand gestures at high accuracy. However, there was one participant with whom the device had lower recognition accuracy. Figure 11 shows a confusion matrix showing the results of the recognition accuracy from that participant. Misrecognition between gestures 5 and 9, which are similar, occurred. We found that there is a possibility of misrecognition in such a case.

6. LIMITATIONS AND FUTURE WORK

There are limitations with the proposed system. First, since the state of deformation of the skin varies from person to person, learning data cannot be reused among users. Also, even if the same user removes the device and then re-attaches it, it is difficult to use the learning data that was recorded in the past due to the user drastically changing the placement of the device. These problems have also been mentioned in the study by Lin et al. [7]. Also, if the skin of the user's hand is thick, the skin does not deform distinctively, so it is often difficult to recognize gestures with our system.

The data obtained from the photo-reflective sensors differ depending on the skin color of the user. Our trial also shows that the accuracy varies depending on the thickness of the hand. It is necessary to adjust the gain according to skin color and thickness of the hand. Currently, there is only one device size. For future work, we will prepare multiple sizes to fit different hand sizes. During this study, we decided on and implemented the number of hand gestures, but we will develop a system that can continuously measure bending and other hand movements. Therefore, it is necessary to increase the number of photo-reflective sensors from the current 13.

7. CONCLUSION

We proposed a recognition system for detecting hand gestures using photo-reflective sensors. The system consists of a wearable device that has photo-reflective sensors set in an array. The sensors measure the deformation of the skin on the back of the hand. Our system supports 20 hand gestures using an SVM. Through a user study, we measured the accuracy of hand-gesture recognition. We found that our system performs at a suitable level of accuracy.

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