International Conference on Artificial Reality and Telexistence
Eurographics Symposium on Virtual Environments (2017)
R. Lindeman, G. Bruder, and D. Iwai (Editors)

3D Reconstruction of Hand Postures by Measuring Skin Deformation on Back Hand

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Abstract

In this research, we propose a method for reconstructing hand posture by measuring the deformation of the back of the hand with a wearable device. The deformation of skin on the back of the hand can be measured by using several photo-reflective sensors attached to a wearable device. In the learning phase, our method constructs a regression model by using the data on hand posture captured by a depth camera and data on the skin deformation of the back of the hand captured by several photo-reflective sensors. In the estimation phase, by using this regression model, the posture of the hand is reconstructed from the data of the photo-reflective sensors in real-time. The posture of fingers can be estimated without hindering the natural movement of the fingers since the deformation of the back of the hand is measured without directly measuring the position of the fingers. This method can be used by users to manipulate information in a virtual environment with their fingers. We conducted an experiment to evaluate the accuracy of reconstructing hand posture with the proposed system.

CCS Concepts
•***Human-centered computing*** → *Interaction devices;*

1. Introduction

Methods for reconstructing hand posture have been studied. Measuring hand posture is important because it can be applied to virtual reality systems and user interfaces. There are two common methods: camera-based and glove-type. Camera-based methods enable hand posture to be recognized without limiting user movement because there is no need to wear a device [WP09]. However, there are restrictions regarding the place of use since cameras need to be installed and this method often has occlusion problems. Glove-type methods can recognize hand posture without occlusion, but the glove may limit hand movement [KJP02] [XNA17].
In contrast with these two methods that measure the hand itself, there are methods that indirectly measure hand posture. There have been many proposals for devices that are worn on the fingers [MCA99] [OSOI12], those that wrap around the wrist [DP14] [FWG*11] [GYI16], and those that wrap around the forearm [TL17] [ZH15] [ZXH16]. 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 our previous study, we focused on the back of the hand [SNK*17]. Since the muscles and bones on the back of the hand are linked to the fingers, finger movements can be clearly observed. This area is less affected by the wearing of clothing compared with a device attached to the wrist or forearm. Therefore, we prototyped a system that consisted of a recognition method for detecting hand gestures by measuring the skin deformation on the back of the hand by using photo-reflective sensors. The system also consists of a wearable device we developed that has several photo-reflective sensors arranged in an array. These sensors enable the distance of an object from sensors to be measured by emitting infrared light and measuring the intensity of the reflected light. Using the sensor data, gestures are identified by using a support vector machine (SVM). There is a device for measuring the back of the hand by using strain gauges [LWH*15], but our method is more durable and easier to equip. However, our previous system focused only on recognizing discrete hand gestures.
In this paper, we propose a system that continuously re-constructs hand posture (Figure 1). Since this system simultaneously records

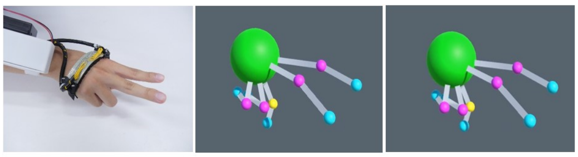

Figure 1: *Prototyped device can reconstruct 3D hand postures.*

the hand shape by using a camera based hand tracking device, Leap Motion, in the learning phase, the user can record continuous hand postures. In the learning phase, we use a depth camera to measure hand postures. At the same time, we measure the deformation of the back of the hand by using photo-reflective sensors. This system estimates hand posture on the basis of regression analysis. Our system can construct a regression model that estimates the posture of the hand from the data of several photo-reflective sensors. The system further displays a reconstructed digital hand as a posture-recognition result.
Here is a summary of our contributions.

- We propose a method that continuously reconstructs hand posture with a small number of real-world sensor data.
- We evaluate the accuracy of a prototype system.
- We design several example application scenarios for our sensing system.

2. Related work

2.1. Motion recognition using photo reflective sensors

Photo-reflective sensors are used in various situations [SII12] [SKW*11]. There are various approaches to estimating body motion by measuring the deformation of the human skin with photo-reflective sensors. AffectiveWear is an eyewear device that can recognize human facial expressions with multiple photo-reflective sensors attached to glasses frames [MSO*16]. Nakamura et al. proposed a device with one photo-reflective sensor that intuitively and seamlessly controls augmented reality information by using the natural movements of eyebrows that users make when they try to focus and stare at something [NM10]. Makino et al. proposed a method for sensing skin deformation on the forearm by using photo-reflective sensors [MSOI13]. Ogata et al. applied the system in [MSOI13] to a user interface [OI15] [OSM*13], and Nakatsuma et al. developed a sensor system that can track finger motion on the back of the hand by using photo-reflective sensors and that is used as an input interface [NSM*11]. Our research aim was to measure the deformation of the skin of the back of the hand by using photo-reflective sensors and identify hand gestures.

2.2. Device-driven approaches of hand posture recognition

Sensors that measure hand movement by placing sensors on the whole hand are commercially available and are being used in various situations [KJP02] [XNA17]. However, natural hand movement may sometimes be restricted.
There have been attempts to simply identify human gestures by reducing the mounting area and location of devices. Researchers have proposed a method for recognizing gestures by using sensors worn on only a finger. iRing is a ring-shaped device with light sensors mounted around it, with which it is possible to measure a user's finger-bending motion [OSOI12]. Chan et al. identified hand gestures by using a camera equipped with a fisheye lens on a ring [CCH*15]. Kashiwagi et al. enhanced the system in [CCH*15] to reconstruct a continuous hand posture sequence by using 3D models of a digital hand when a user grips objects [KSM*17]. Kim et al. developed a wrist-worn device that can measure finger movement by using an emitted IR laser and IR camera [KHI*12]. 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 in blood flow when the finger is bent [MCA99]. Achibet et al. proposed a method for reconstructing the posture of a human hand by using information on the contact points of a tablet PC [ACLM15]. Harrison et al. developed a system that can recognize gestures when a user places a characteristic hand shape on a touch display [HXSH14]. Users can switch digital tools based on gesture sets.
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 wrapping devices around the wrist. Fukui et al. proposed a method for measuring wrist-shape deformation by using photo-reflective sensors placed inside a wristband [FWG*11]. 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 [DP14]. GestureWrist uses capacitive sensors to recognize a small set of gestures [Rek01]. WristWhirl is a wristband-type device that can recognize dynamic hand gestures by using multiple piezoelectric sensors attached around the band [GYI16].
There are several methods for identifying gestures by attaching devices to a user's forearm. The Myo armband [TL17] uses electromyography to recognize hand gestures by measuring the movement of the muscles of the forearm that are relevant to moving the hand and fingers. Zhang et al. proposed a method of estimating the positions of the bones of the hand and fingers by using tomography [ZH15] [ZXH16]. However, these methods have limitations regarding the number of available gestures.
There is a system for estimating hand posture by using depth cameras and regression models. This method does not require attaching optical markers on the hand [HHH16]. However, there are restrictions regarding the place of use since cameras need to be installed and this method often has occlusion problems.

3. Proposed method

We obtain the relationship between the deformation of the back of the hand and the finger posture by using a multivariate and multivariable regression model to estimate the finger posture from the deformation of the back of the hand (Figure 2). Multivariate and multivariable regression analyses are statistical methods for estimating a relational expression, called a "regression model", that expresses the correlation between two certain continuous variables. We can estimate the value of one variable from the value of the other variable by using the estimated regression model.
Our method has two phases: a learning phase and estimation phase. At the learning phase, we measure the deformation of the back of the hand and the finger posture simultaneously by using measurement devices. We reduce the dimension of the measured data. Then, the regression model learns the relationship between the deformation and the posture by using the dimensionally reduced data. At the estimation phase, we measure only the deformation of the back of the hand. After reducing the dimension of the sensor data, we can estimate the dimensionally compressed finger posture with the regression model. Then, we obtain the finger posture that has the original dimensions by using the dimension restoration in real-time.

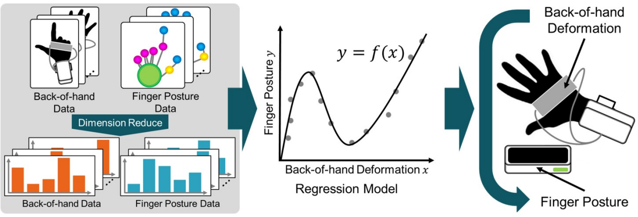

Figure 2: *Proposed method of reconstructing hand posture using regression model.*

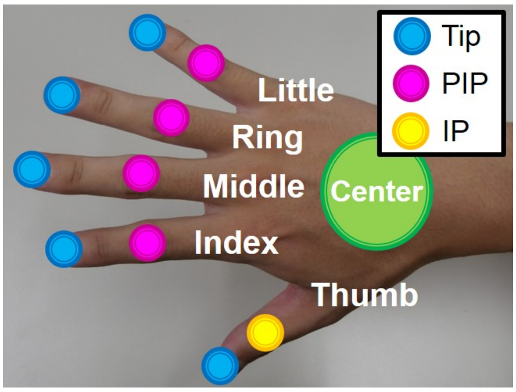

Figure 3: *Hand labels defined in this research.*

We apply the finger posture to the hand shape in a virtual environment in order to reconstruct the posture in the real environment.

3.1. Measuring hand posture and skin deformation

We use Leap Motion to measure finger postures in the learning phase. Leap Motion tracks the position and angle of fingers using two IR cameras and three IR LEDs [LM17]. The tracking accuracy of Leap Motion is 0.01 mm in the space of about 3-60 cm. Leap Motion is the system that can track fingers without markers and be easily installed. So in this study, we measure finger postures using it. We decided to use the position information of 10 joints: the fingertips of each finger, the interphalangeal (IP) joint of the thumb and the proximal interphalangeal (PIP) joints of from the index finger to the little finger (Figure 3). We measure the 3-dimensional relative position of these joints from the hand center to acquire 30-dimensional data. We measure the deformation of the back of the hand and acquire 13-dimensional data by using the wearable device developed in [SNK*17]. The device takes measurements with photo-reflective sensors that can measure distance with infrared rays.

The infrared light of Leap Motion is stronger than that of the photo-reflective sensors, so the sensors get a sensor value with noise. To remove the noise, we measure the values of the sensors five times and acquire the minimum value of them. The reconstructed back-of-hand data is not smooth and stable because it has a high frequency, minute fluctuation. Also, the finger-posture data captured by Leap Motion is also not stable because it has noise. These noise has a large influence on estimation accuracy. For this reason, we remove the noise from measured data by filtering the measured back-of-hand data and finger posture data with a low pass filter with an IIR filter. In our method, the cutoff frequency is 0.84 Hz for back-of-hand data and 1.78 Hz for finger posture data.

3.2. Dimension reduction of data

We reduce the dimension of the back-of-hand data from the 13th to the 5th dimension and finger posture data from the 30th to the 5th dimension to convert them into data expressed by uncorrelated variables. The number of combinations that can be represented by the data increases dramatically as the dimension of data increases. As a result, regression models require very much training data for learning and they cannot learn with sufficient accuracy with finite data. To resolve this, we use principal component analysis (PCA) and reduce the dimensions by referring to [SKMA12] [ATK*08]. The regression model learns the relationship between the deformation of the back of the hand and the finger posture by using the dimensionally reduced data of the back-of-hand and the finger posture.

3.3. Constructing regression model

In a preliminary experiment, we investigated nonlinear ridge regression, support vector regression, Gaussian process regression, random forest regression, and gradient boosting regression as the regression models. As the result, we decided to use random forest regression (RFR) with the highest coefficient of determination in the preliminary experiments.

RFR is a regression model using a random forest which is ensemble learning with a decision tree as a weak learner. We generate B sets of sub-samples from the dataset by random sampling and create B decision trees from each of them. When splitting each node during the construction of the tree, we randomly select m variables from M explanatory variables of sub-samples and choose a split that is best among all features by split function. To estimate the finger posture, we estimate with the learners and calculate the average of all estimated results. In our method, $B = 64, m = \sqrt{M}$, $M = 30$ for finger posture data, $M = 13$ for back-of-hand data.

4. Implementation

4.1. Hardware

In our previous study [SNK*17], we prototyped a device to detect hand gestures by measuring the skin deformation on the back of the hand by using photo-reflective sensors (Figure 4). We placed 13 photo-reflective sensors in a straight array at 5.1 mm intervals (Figure 5). Our device contains trapezoid components to make a gap between the sensors and skin (Figure 6). 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 by using Velcro tape. Therefore, the user does not need to use special tools when wearing it.

We used the SG-105 photo-sensors manufactured by Kodenshi Co., Ltd. The 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 a wireless module. The device also has AAA batteries for driving the sensors, mi-

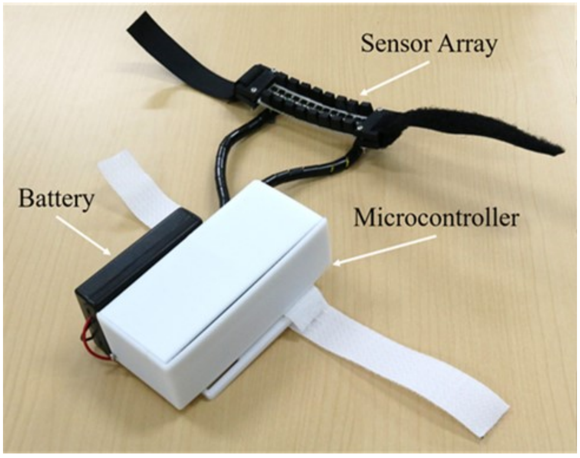

Figure 4: *Overview of hardware device [SNK*17].*

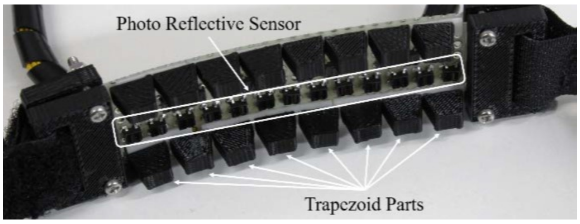

Figure 5: *Photo-reflective sensor array [SNK*17].*

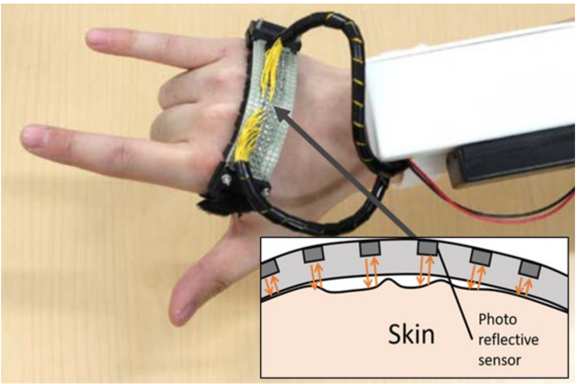

Figure 6: *Principle of proposed sensing method [SNK*17].*

crocontroller, and XBee. Therefore, we can use the system without having to extend the wiring to the outside.

4.2. Software configuration

Our system consists of Unity software and Python software (Figure 7). With Unity, our system reads the back-of-hand data by using the wearable device and finger posture data by using Leap Motion and visualizes them. With Python, our system reduces the dimensions of the back-of-hand data and the finger posture data, makes a regression model, and estimates finger posture data.
The Unity software communicates with Python with HTTP commands. When Unity sends the back-of-hand data and corresponding finger posture data to Python in the learning phase, Python reduces the dimensions of the sent data with PCA and learns an RFR model. When Unity sends a sensor value to Python in the estimation phase, Python estimates the finger postures on the basis of the data generated by the dimensionally reduced sensor value with the RFR. The estimation result is data in which the dimensions of finger posture are reduced. Therefore, after reconstructing the dimensions, we obtain the finger posture data for the original dimensions. Python returns the estimation result to Unity, and Unity then visualizes the posture of the finger in the hand shape. Our system works at a frame rate of 50 fps and is able to send sensor values to Python and reconstruct a finger posture in 2 - 20 msec. We use PCA and RFR implemented in the scikit-learn library.

5. Evaluation

5.1. Procedure

We evaluated the accuracy of the finger postures reconstructed by the proposed method. The participants included seven men and two women (all Japanese, average 22.8 years old, average hand length 182.3 mm, average hand width 77.55 mm, average wrist circumference 157.5 mm). Participants fixed the position of their right arm on a table during measurement. We measured the deformation of the back of their hand with the wearable device, and at the same time, we measured the finger posture with Leap Motion. We measured two types of finger postures: the static-state finger posture and dynamic-state one. In the static-state, we measured ten sequences of finger posture and deformation of the back of the hand per participant to acquire data of 2500 frames (= 50 fps $\times$ 5 seconds $\times$ 10 sequences). For the first, the participants extended only the index finger and held this finger posture for 10 seconds. Later they sequentially opened and held their middle finger, ring finger, little finger, and thumb every 10 seconds. We divided each of this sequences into sequences for 5 seconds and finally obtained ten sequences in total. In the dynamic-state, we measured four sequences of finger posture and deformation of the back of the hand per participant to acquire data of 2000 frames (= 50 fps $\times$ 10 seconds $\times$ 4 sequences). The participants first extended only their index finger. Then, they opened their middle finger, ring finger, little finger, and thumb in order each second. They performed this operation eight

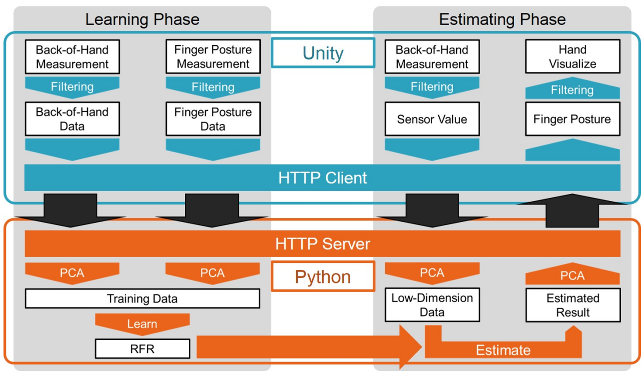

Figure 7: *Overview of system configuration.*

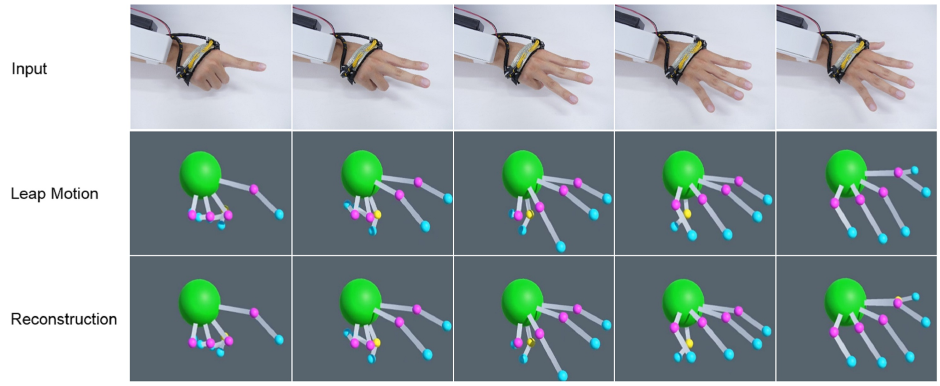

Figure 8: *Results of reconstructing hand posture. Top: Samples of hand posture in a real environment, Middle: Hand posture measured by Leap Motion, Bottom: Hand posture reconstructed by our method.*

times. We measured this sequence and divided it into sequences for 10 seconds and finally obtained four sequences in total.

We evaluated estimation errors with acquired sequences for each participant. We performed ten-fold cross-validation in the static-state and four-fold cross-validation in the dynamic-state to calculate the estimation error. We separated the sequences into one sequence as test data and the remaining sequences as training data, and we repeated this until all sequences were used as test data once. We calculated and acquired the temporal transition of estimation errors with the 3-dimensional Euclidean distance between each joint position of the finger postures with Leap Motion and the position of the postures with our method. We also calculated the mean errors of the transition for all participants.

5.2. Results

We show the temporal transition of the estimation error of the static-state finger posture for one participant (Figure 9). Since the fingers are about 10 - 15 mm thick for adults, Figure 9 shows that our system can estimate the finger posture from the middle finger to the little finger when held in the static-state with sufficient accuracy. The mean error in the finger posture estimation for all participants is as shown in the Figure 10. The average estimation error for all joints was about 3.34 mm. As shown in Figure 11, the errors may reach 50 mm in some sequences, which lead to error in estimating finger postures, and the variance of the error increased for the thumb and index finger posture. This is because our system cannot exclude some of the noise of the sensor values with noise processing or the low pass filter processing, and this influenced the learning of the regression model.

We show the temporal transition of the estimation errors for one participant in the dynamic state in Figure 12. The estimation error of finger posture of all participants in this state showed an estimation error trend like that in Figure 12. The figure shows that the posture estimation errors for the thumb and index finger were large relative to the thickness of the fingers at around the 200th frame and 450th frame. At these frames, the participants were opening and closing the thumb. This is because our device could not directly measure their thumb posture from the deformation of the back of their hand but indirectly by the deformation around their index finger, and the back-of-hand data contained little information on the deformation of the thumb's tendon. Furthermore, the thumb postures slightly deformed the back of the hand near the index finger,

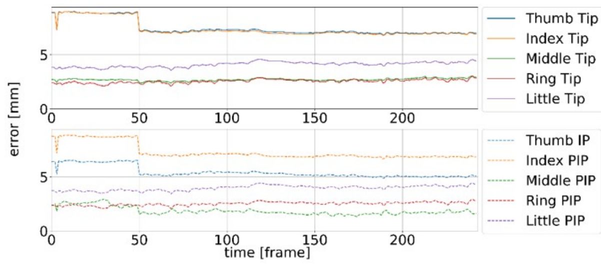

Figure 9: *Example estimation errors of finger joints in the static state. The estimation errors change in the range of about 2 - 8 mm.*

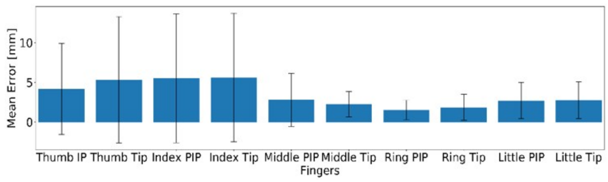

Figure 10: *Mean estimation errors of finger joints in the static state. The whiskers are variances of errors.*

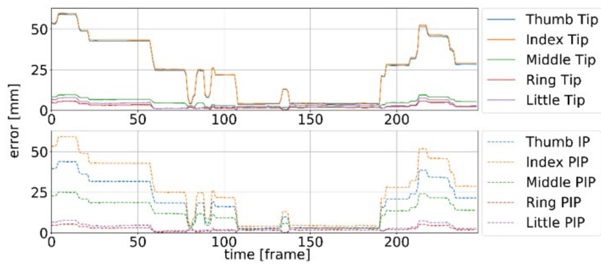

Figure 11: *Example of large estimation errors of finger joints in the static state.*

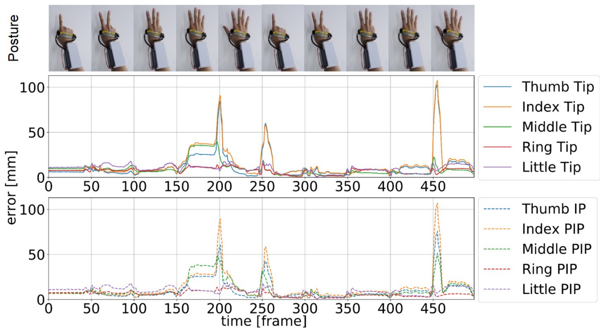

Figure 12: *Example estimation error of finger joints in the dynamic state.*

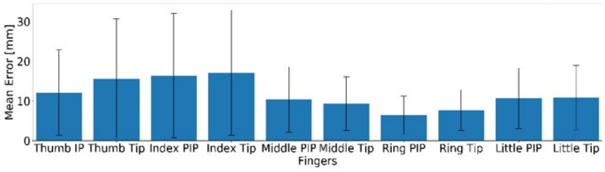

Figure 13: *Mean Estimation errors of finger joints in the dynamic state. The whiskers are variances of errors.*

which will greatly affect the accuracy of estimating the index finger posture.

The overall posture estimation error was large relative to the thickness of the finger. We think that this is because of the low spatial resolution of the photo-reflective sensors and because the sensors could not measure minute changes in the back of the hand sufficiently when the fingertips moved.

6. Applications

The proposed method estimates the finger posture from the deformation of the back of the hand, so it can reconstruct the hand shape of users and use it for interaction and a user interface in a virtual reality environment.

6.1. VR application

Our device can be used in applications in which users can manipulate displayed information by using their hands in VR space (Figure 14). Since the hand posture is reconstructed and visualized in a virtual environment in real time, users can perform manipulation naturally. In previous methods, users interacted with a virtual environment with a hand-held controller [OV17]. Although this method makes it possible to interact with a virtual environment by using the position and angle of hands, it is necessary to prepare operations or commands such as with controller buttons in order to realize various operations using fingers such as grasping or throwing an object. Also, other methods that use data gloves required time and effort to wear and may interfere with the natural movement of hands. The proposed method does not require users to hold a controller, so users can interact with their fingers freely. This convinces us that interaction with a virtual environment can be performed intuitively and diversely as in real environment and that immersion in VR will improve.

6.2. Puppet control

We believe that the proposed method can manipulate a 3D model in a virtual environment with various finger actions, and this would be especially suitable for virtual puppet operation (Figure 15). In real environments, users operate puppets by using the fingers, such as by manipulating threads or bars or by attaching the puppets directly them to the hands or fingers. Our system can also apply this metaphor of puppet manipulation in a real environment to the virtual environment. In detail, hand shapes are reconstructed with the proposed method, and the position of each finger is associated with the position of the joints of a 3D model in a virtual environment. We believe that it is possible to manipulate virtual objects as well as real objects by using the proposed method, so our system is not limited to 3D model operations.

Figure 14: *VR application with our prototyped device. The user grasps a boll in a virtual environment with their finger motion.*

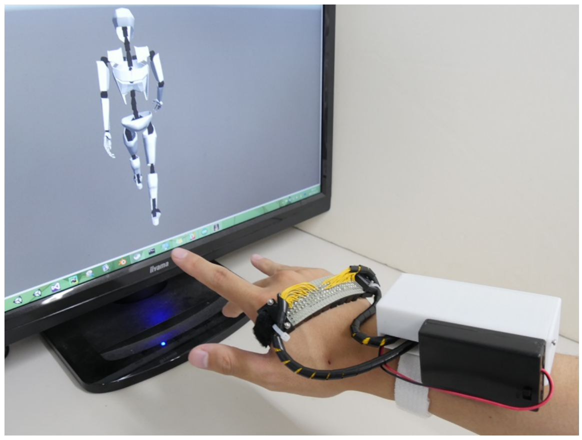

Figure 15: *Concept image of puppet application. The user manipulates the left leg of the 3D model in a virtual environment with the index finger of their right hand.*

7. Limitations and future work

In this research, photo-reflective sensors measured the deformation of the back of the hand. Since each user has a different distance between the sensors and the back of the hand, it was difficult to share a regression model among users. Therefore, it is necessary to learn and generate a regression model for each user. If our system accumulates a large amount of learning data sets and understands the tendency of the hand skin deformation, it can fit a specific model to each user, so our system will require only simple calibration. If we understand the tendency of skin deformation of the back of the hand by analyzing a large amount of data that measure various physique and race participants, we can improve the finger posture estimation algorithm. Furthermore, by analyzing the tendency for each participant, we might convert raw data into data which does not affect the tendency of the skin deformation of the back of the hand between the individuals.

Even if the same user wears the device, the posture estimation accuracy decreases due to misalignment of the device during use or there being different mounting positions due to re-attaching the device. Therefore, the system always needs to learn a model when a user re-wears the device. Also, our wearable device measures the deformation of the skin by using 13 photo-reflective sensors, so it cannot measure the entire deformation of the back of the hand with sufficient accuracy. For example, the device cannot measure directly the deformation around the thumb, but it can do so indirectly near the index finger. This affects the posture estimation accuracy. In addition, the thumb posture deforms the back of the hand near the index finger, which also greatly affects the accuracy of the index finger. This problem can be solved by improving the number and arrangement of sensors of our device. As future work, we would like to increase the number of the sensors and re-arrange them on the back-of-hand measurement device to improve accuracy for the thumb and index finger, and we would like to make the system robust against problems with re-attaching the device and against individual differences.

The device measures the deformation of the back of the hand with infrared light. Leap Motion also measures the finger posture with infrared light. Therefore, the device obtains sensor values with noise due to infrared light emitted by Leap Motion. We believe that this problem can be solved by measuring the deformation with an electromyogram or measuring the finger posture with other systems like OptiTrack [Nat17].

8. Conclusion

We proposed a method for reconstructing the finger posture from the deformation of the back of the hand by using the wearable device developed at [SNK*17]. We use a regression model to express the relationship between the deformation of the back of the hand and the finger posture with the training data, and we estimate the finger posture from the deformation by using the model. We conducted user experiments and evaluated the finger posture estimation error for the measured finger posture data. As a result, the estimation of the finger posture in a static state had an error of 2 - 4 mm on average for the finger posture measured by Leap Motion. Our method can estimate the posture from the middle finger to little finger with sufficient accuracy, but the estimation errors of the thumb and index finger were large in some cases. The posture estimation of the fingers in the dynamic state had an average error of 7 - 17 mm compared the finger posture measured by Leap Motion.

This research can be used as an operation method in VR environments. In the future, we will improve the accuracy of estimating finger posture by improving the type, number, and arrangement of sensors. Also, we are planning to develop a system that is robust against problems with re-attaching the device and that accounts for different types of user.

Acknowledgements

This work was supported by JSPS KAKENHI Grant Numbers JP16H01741, JP16H05870.

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