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GestEarrings: Developing Gesture-Based Input Techniques for Earrings

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Abstract— **In recent years, wearable computing has become popular in society, and demand for devices that look comfortable when worn or operated has been increasing. Until now, various items such as hats, hair extensions, and masks have been developed as interfaces. In this study, we propose a method to turn earrings into a gesture input interface. Earrings are widely used as a fashion item, and we believe that the appearance and wearability of earring devices are socially acceptable. First, we explored user-defined gestures using three types of earrings with different shapes and characteristics. Next, we implemented earring devices capable of identifying each of the determined gesture sets. The gesture recognition rate for each earring was 83.6% (hanging earring/11 types), 96.6% (surface earring/8 types), and 87.0% (hoop earring/12 types).**

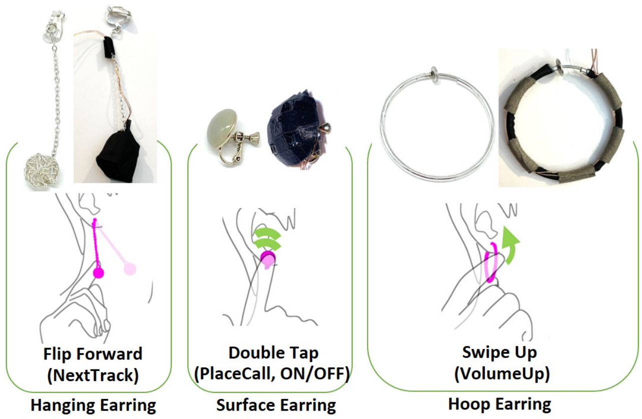

Fig. 1. User-defined gestures were constructed for three types of earring shapes, and gesture identification experiments were conducted using the created earring devices.

I. INTRODUCTION

Wearable devices, such as smartwatches and smart rings, have seamlessly integrated into daily life, offering functions such as fitness tracking, sleep monitoring, and notification alerts, thereby enhancing the convenience of everyday tasks. IDC predicts that the market for wearable devices will increase in size for several years [1]. Technological advancements, such as smaller size and longer battery life, contribute to the integration of wearables into everyday life.

Furthermore, the design and form factor for wearable devices is important for everyday use. When integrated into commonly used items in daily life, these wearables become more comfortable, socially acceptable, and user-friendly. This has led to ongoing research into incorporating wearable technology into various accessories, including jewelry [2], masks [3], [4], hats [5], glasses [6], [7], and hair extensions [8].

The widespread adoption of accessories that seamlessly blend functionality with fashion, akin to jewelry, could significantly enhance the potential of wearable devices. Buruk et al. developed a prototype design tool that aims to intersect functionality and aesthetics by focusing on smart jewelry design [9]. Another Walczak et al. study focuses on jewelry's social and cultural connotations [10]. However, these studies have not examined the possibility of gesture input interaction with earrings.

In this study, we focus on earrings, a common type of everyday jewelry. Earrings are widely accepted as a fashion item, making them ideal for wearable technology form factor. Moreover, the act of using earrings for input is discreet and unlikely to attract attention, seamlessly blending into normal behavior. Furthermore, using earrings for gesture-based input offers the advantage of eyes-free operation, enabling users to input information without needing to look at a screen.

We conducted two experiments, gesture search and gesture identification to explore the possibility of earring devices and to evaluate their accuracy as devices. First, to explore gestures using earrings, we conducted an experiment in which users invented gestures and constructed a set of gestures. Next, we evaluated the accuracy of gesture identification by using the earrings as a gesture input device.

The contributions of this study are as follows.

- We constructed user-defined gesture sets for three types of earrings.
- We implemented three types of earring devices (hanging earrings, surface earrings, and hoop earrings). We designed the prototypes to match the form factors of the existing earrings.
- Through a user study (N=10), we show that our devices achieve 83.6% (hanging earring/11 types), 96.6% (surface earring/8 types), and 87.0% (hoop earring/12 types) average identification accuracy.

II. RELATED WORK

A. Input Interfaces with Accessaries

Several studies have utilized accessories such as hats, hair extensions, glasses, and masks as input interfaces. Dierk et al. [5] designed a wearable device that uses a hat to communicate with the wearer; Vega et al. [8] used capacitive

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touch sensors to turn hair extensions into input devices. Masai et al. [7] and Futami et al. [6] proposed glasses which have photo-reflective sensors to enable eye-based interaction. Yamamoto et al. [4] proposed methods to transform a mask's strap into an input interface. SilentMask [11] and E-MASK [12] are mask-shaped interfaces for silent speech interaction.

Among accessories, some researchers have proposed input interfaces using jewelry, including earrings. Futami et al. [13] proposed a facial expression recognition method using earrings. An optical sensor is integrated into the earring, and the distance between the earring and the surface of the face is read to detect facial expressions. Arora et al. formulated a design space for information input using jewelry and explored this space using earrings [2].

This study aims to create earrings as an intuitive and user-friendly gesture-based input device. While Arora et al.[2] proposed a design space for earrings, their gestures were researcher-defined. User-defined gestures offer a more comfortable interface. Furthermore, the method by Futami et al.[13] requires changing facial expressions to input information, which can be impractical in public or during conversations due to attracting attention. In contrast, our method allows information input through earring movement, ensuring a discreet interaction process.

B. Gesture Elicitation Study

Numerous gesture elicitation studies have been conducted to define gesture sets. Wobbrock et al. defined gesture sets for surface computing by conducting a gesture elicitation study (GES), in which the researchers assigned the tasks (referents) to participants, and the participants invented the gestures [14]. Some studies show that user-defined gesture sets are preferred and more memorable compared to those defined by a researcher [15], [16].

Gesture elicitation studies have been conducted in a variety of design spaces [17]. Gesture elicitation studies have been conducted on various body parts: face [18], nose [19], one hand [20], hand-to-face [21], fingers [22], foot soles [23], and ears [24]. Elicitation studies have also been conducted for specific situations or objects, such as TV interaction [25], hand-peripheral screen interaction [26], air gestures for spreadsheets [27], and squeeze gestures for a cushion [28]. There are also examples of gesture elicitation studies for fashion accessories. Dierk et al. explore the interaction modality for hats [5], and Yamamoto et al. identified a set of gestures on mask straps [4].

However, user-defined gestures for earrings have yet to be explored. In this study, we specifically conducted the experiments to explore the user-defined gesture sets using earrings.

III. GESTURE EXPLORING STUDY

To create a user-friendly gesture set for earrings, we conducted an experiment to explore preferred gestures by users. The gesture set constructed in this section is used in the user experiment (Section V) to evaluate the performance of the earring device. In this study, we used three types of earrings with different shapes and characteristics. By investigating three typical earring shapes, we explored the possibility of gesture input with earrings.

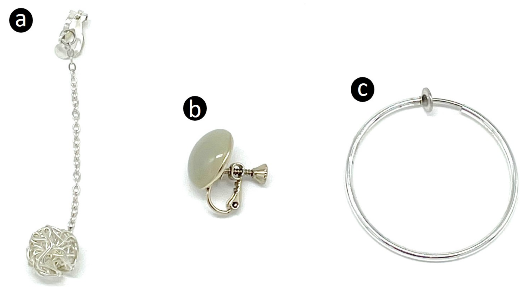

Fig. 2. Three types of earrings were used in this study. a: hanging earring, b: surface earring, and c: hoop earring

A. Experiment Overview

Twenty participants (13 males and 7 females) with a mean age of 22.9 years (SD = 1.7 years) participated in the experiment. One participant was left-handed, one was ambidextrous, and the other 18 were right-handed.

After answering their name, age, gender, dominant hand, and frequency of earring use, participants were asked to wear the earrings and watch a video or images about the operations. They were then required to design a gesture for the operation using the worn earring. In the experiment, we used three types of earrings: hanging earrings, surface earrings, and hoop earrings, shown in Figure 2. The list of operations (called referents) was shown in Table I. All operation was divided into four groups: phone group, music group, application/item selection, and screen operation. The application/item selection direction (right-left-up/down) is a discrete operation, like moving to the next item, whereas the screen operation direction (scroll right-left-up/down) is a continuous operation, like moving the display location in a map application. All participants followed a standardized sequence for devising gestures, starting with phone group, music group, application/item selection, and finally, screen operations. Participants could change the gesture later if necessary. Each group moved on to the next group after all the gestures had been devised in all the layers. After designing all the group's gestures, the participants changed the type of earring. The order of earrings was also standardized for all participants: hanging earrings, surface earrings, and hoop earrings in that order. The following rules were set at the time of the design.

- Gestures must be in contact with the earring.
- Gestures should not be shared between operations within the same group. The same gesture can be used for different groups.
- No technical limitations need to be considered.

After devising gestures for all the earrings in the group, the participants were asked about the ease of performing each

TABLE I

TARGET ACTIONS FOR GESTURE ELICITATION STUDY

Groups	Referent
Phone	Take a Call / Hang Up a Call Ignore a Call Place a Call
Music	Pause or Play Volume Up Volume Down Next Track Previous Track
Applications / Item Selection	Right Left Up Down Select ON / OFF
Screen Operation	Scroll Right Scroll Left Scroll Up Scroll Down Zoom In Zoom Out

gesture. For all operations, the ease of performing the gesture in each earring was asked on a 5-point scale (1: difficult, 3: standard, 5: easy). The results of these subjective evaluations were utilized exclusively to inform the determination of the gesture set detailed below.

B. Final Gesture Set

As a result of the experiment, we finally determined the gesture sets for each earring as shown in Figure 3. The decision method was a majority vote of gestures for each operation. When multiple gestures were tied for first place in the majority vote, the gesture with the highest value was selected by comparing the subjective evaluation values of ease of use given by the participants in the experiment on a 5-point scale. When the same gesture ranked first in operations within the same group, the gesture was assigned using the optimization method proposed by Tsandilas et al [29].

1) Hanging Earring: Figure 3a is a gesture set with hanging earrings, and a total of 11 different gestures were obtained. Gestures other than “tap clasp” which taps the metal fittings in the earlobe area, are gestures that touch the sphere area. “Tap” is a gesture to tap the sphere with the index finger after pinching it. “Flip forward” and “Flip backward” are gestures to flip the sphere part. “orb glide left”, “orb glide right”, “orb glide up”, and “orb glide down” are gestures to move the sphere in each direction. Each direction follows the wearer’s head coordinate system. The “twist clockwise” and “twist counterclockwise” are gestures to pick up the sphere and rotate it in the direction shown in Figure 3a. “pinch” is a gesture to pinch a spherical part.

2) Surface Earring: Figure 3b is the gesture set with surface earrings, and we obtained a total of 8 different gestures. All gestures are gestures to touch the surface of the earring. The “tap,” “double tap,” and “long tap” gestures all tap the surface of the earring and differ in frequency and duration. The “swipe counterclockwise,” “swipe up,” “swipe down,” “swipe right”, and “swipe left” gestures are used to trace the earring surface. Each direction follows the coordinate system of the wearer’s head.

3) Hoop Earring: Figure 3c shows the gesture set for the hoop earring, and a total of 12 gestures were obtained. Most of the gestures were tracing the hoop and moving the hoop. “Tap” is a gesture to tap the bottom of the earring. “Swipe up” is a gesture that uses a single finger to trace from the bottom of the earring forward to the top. “Swipe down” gesture is the reverse of the “swipe up” gesture, tracing from the top of the earring forward to the bottom. “Pinch out” and “pinch in” are tracing gestures using two fingers. “Pinch out” is traced from the bottom of the earring to the top, and “pinch in” is traced from the top of the earring to the bottom. “Pinch & glide forward,” “pinch & glide backward,” “pinch & glide right”, and “pinch & glide left” are gestures to pick up and move the hoop. Each direction follows the wearer’s head coordinate system. “Pinch” is a gesture to pinch the lower part of the earring with a finger, and “pinch & glide around the ear” is a gesture to rotate the earring until it touches the ear.

C. Cognitive Process

We delve into the cognitive processes of participants concerning gestures involving earrings. Users suggested numerous gestures involving the movement or tracing of the earring. Since the earrings were not visible during performing gestures, it is presumed that many of the proposed gestures were executed effortlessly without the need for visual guidance. Our experiments also revealed that users tended to suggest symmetric gestures for inherently symmetric operations.

IV. Implementation

This section presents a pipeline comprising both hardware and software, designed to facilitate the recognition of the gesture sets developed in the previous section.

A. Hardware

In creating the three earring devices, sensors were determined and placed so that the determined set of gestures could be identified. The sensor’s data, converted from analog to digital by a 3.3V Arduino Pro Mini, was then transmitted to a PC.

1) Hanging Earring: For hanging earrings, we integrated a 9-axis sensor (3-axis acceleration, 3-axis angular velocity, and 3-axis magnetism, BNO055 from Adafruit) to capture movements such as swaying, spinning, and acceleration. Attaching the sensor to the earring’s lower part with tape, we ensured it did not affect the natural swing movement, using 0.1mm enameled wire for minimal interference(Figure 4a).

2) Surface Earring: To classify gestures involving surface earrings, such as touching, we employed photo-reflective sensors (the SG-105 by Kodenshi). These sensors are crucial for discerning the proximity between the finger and the earring’s surface, which is vital for interpreting gesture-based interactions. Initially, a part of the surface earring

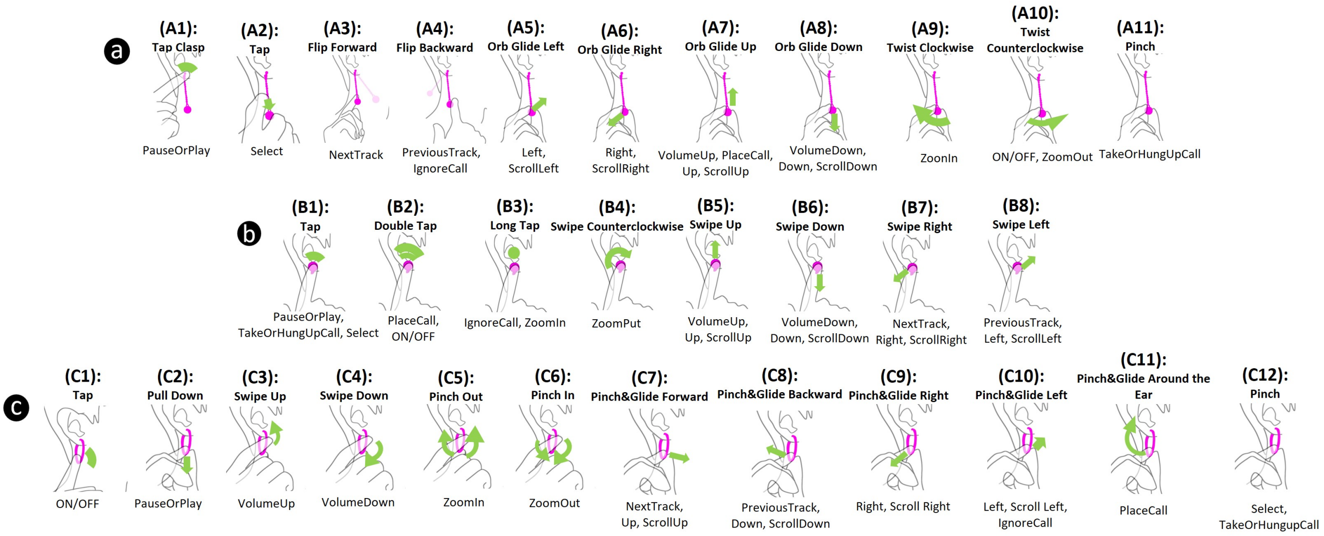

Fig. 3. Gesture set (a: hanging earring, b: surface earring, and c: hoop earring)

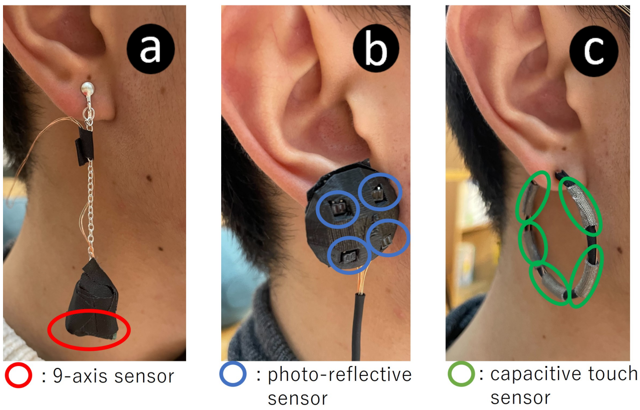

Fig. 4. The wearing of earrings and sensor positions(a: hanging earring device, b: surface earring device, and c: hoop earring device)

was made using a 3D printer, designed for effective sensor integration. The sensors were then installed on the earring's surface through pre-made holes, ensuring the detection of touch gestures. Finally, we attached a screw-spring earring part with a can to the back side of the earring so that the earring can be attached to the ear (Figure 4b).

3) Hoop Earring: For the hoop earring, we used a capacitive touch sensor (MPR121 from Adafruit Industries) to detect the gestures of touching the hoop. A capacitive touch sensor can acquire contact points on the hoop. First, insulating tape is wrapped around the hoop earrings, and five capacitance sheets are placed on top of the tape. Each capacitance sheet is connected to an enameled wire, and the enameled wire is fixed with other capacitance sheets along the hoop shape (Figure 4c).

B. Software

1) Data Collection: The system received the sensor values obtained from each earring device, and output the sensor values for a fixed frame obtained when a gesture was performed as time-series data. The frame rate of each device depends on the sensor used. The communication speed of the hanging earring device was about 18 fps and 20 frames were acquired, so each gesture took about 1.1 seconds. The communication speed of the surface earring device was about 71 fps and 150 frames were acquired, so each gesture took about 2.1 seconds. The communication speed of the hoop earring device was about 10 fps and 20 frames were acquired, so each gesture took about 1.1 seconds. Regarding the timing of the start of gesture data recording, the hanging earring is designed to start recording gesture data automatically. For surface and hoop earrings, a threshold for the difference between consecutive frames was set, and the gesture was initiated when it became larger than the threshold.

2) Gesture Identification: The flow of processing the acquired time-series sensor data is shown in Figure 5. First, the time-series data is divided into 5 segments in the order of the sensor dimension. Statistical features are extracted for each divided segment. This time, we extracted five statistical features: mean, variance, median, maximum, and minimum. Therefore, the number of explanatory variables is the number of sensors $\times$ 5 (number of partitions) $\times$ 5 (number of statistical features). The number of dimensions of the sensor data is 9 for the hanging earrings, 4 for the surface earrings, and 5 for the hoop earrings. To sum up, the number of explanatory variables is 225 for hanging earrings, 100 for surface earrings, and 125 for hoop earrings. The extracted features were used as explanatory variables, and the gesture labels were used as objective variables.

After extracting the features from the acquired time-series sensor data, we used a Random Forest to classify gestures.

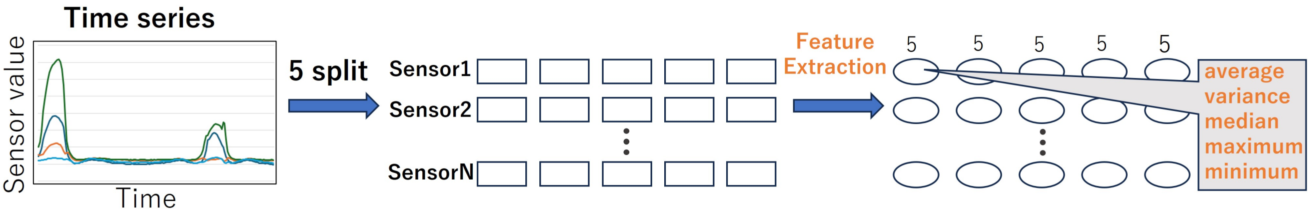

Fig. 5. Feature extraction flow in machine learning for gesture identification.

We used the random forest, which had the best discrimination accuracy among several models (SVC, XGBoost, random forest). The number of decision trees was set to 10, with an unrestricted depth parameter setting.

V. Experiment

A. Experiment Overview

To evaluate the classification accuracy of the implemented devices for the defined gesture sets, we collected the gesture data with ten participants (6 males and 4 females, all 10 right-handed) with a mean age of 22.7 years (SD = 0.7 years). The experiment was conducted in a sitting position in a room. Participants whose hair touched the earrings tied their hair back and participated in the experiment. The gesture sets for each earring device are shown in Figure3. These are the gesture sets determined by the experiment conducted in Section III.

Each participant wore an earring in his or her right ear as shown in Figure4 and performed gestures with all three types of devices. Participants practiced each gesture before beginning data collection to ensure that all gestures were performed correctly. After practice, all gestures were repeated and recorded 20 times in the same order. If a gesture was incorrectly performed, only that gesture was re-measured. After all gesture data were recorded with one earring, the participants switched to the next earring and performed the gesture. The order of the earrings was hanging earrings, hoop earrings, and surface earrings.

To evaluate device identification accuracy and user dependency, we created within-individual and between-individual models and evaluated their average identification accuracy. within-individual identification means that a model is trained using a user's gesture data as training data and the same user's data is used as test data to evaluate the accuracy of identifying gestures. On the other hand, between-individual identification means that a model is trained using gesture data other than that of the user as test data, and the test data is used to evaluate the accuracy of gesture identification.

For the within-individual model, we performed a 10-part cross-validation for each user's data. The gesture identification accuracy of the within-individual model for all users was averaged to obtain the average accuracy of the within-individual model. For the between-individual model, we cross-validated one participant's data as test data. 9 users' data were used as training data, and the performance was evaluated on the remaining one participant's data as test data. The data of all users were used as test data one at a time, and the average identification accuracy was calculated for the between-individual model.

B. Result

The mean identification accuracy in the within-individual models was 83.6% (SD = 6.3%) for hanging earrings, 96.6% (SD = 2.0%) for surface earrings, and 87.0% (SD = 6.1%) for hoop earrings (Figure 6). The mean identification accuracy in the between-individual model was 73.6% (SD = 6.2%) for hanging earrings, 84.4% (SD = 10.5%) for surface earrings, and 69.3% (SD = 8.5%) for hoop earrings (Figure 7). The gesture numbers in the confusion matrix correspond to the gesture numbers in Figure 3.

VI. Discussion, Limitation & Future Work

A. False Gesture Detection

We examine gestures frequently misidentified in the within-individual model (Figure 6). Hanging earring devices often misidentify ”flip forward” and ”flip backward”.

Misidentification is also common among the three gestures “orb glide left”, “orb glide right”, and “orb glide up”. These gestures involve pinching the sphere and moving it in each direction. These findings suggest that while distinguishing between shaking and being pinched is possible, detecting the direction of shaking and movement is challenging.

All gestures were relatively accurate for the surface earring. The earrings utilize four photo-reflective sensors to measure the distance between the surface and the fingertip. Since no object other than the finger comes close to the earring surface, we believe that high accuracy was achieved by capturing the point where the earring is touched.

The most frequently misidentified gestures in hoop earrings were the four movements of the hoop: “pinch & glide forward”, “pinch & glide backward”, “pinch & glide right”, and “pinch & glide around the ear”. These earrings are detected by five capacitive touch sensors that measure finger and cheek contact with the earrings. Since the movement of the earrings was not directly measured, the identification accuracy of the moving gesture was relatively low. The “pinch & glide left’ gesture showed relatively high accuracy among all gestures, but when worn on the right ear, this gesture was distinguishable because the sensor made contact with the neck and cheek, causing a change in capacitance.

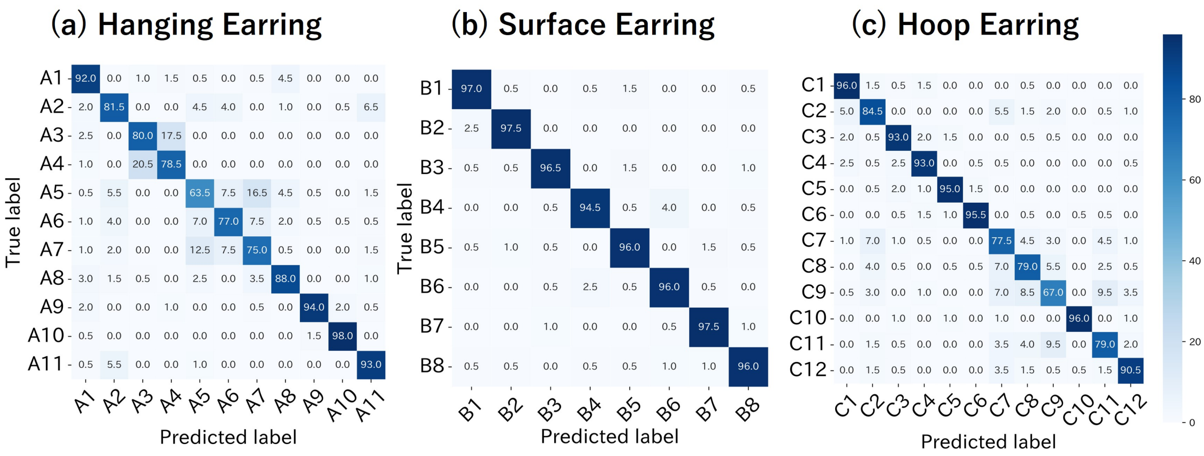

Fig. 6. Confusion Matrix in the within-individual model in each earring.

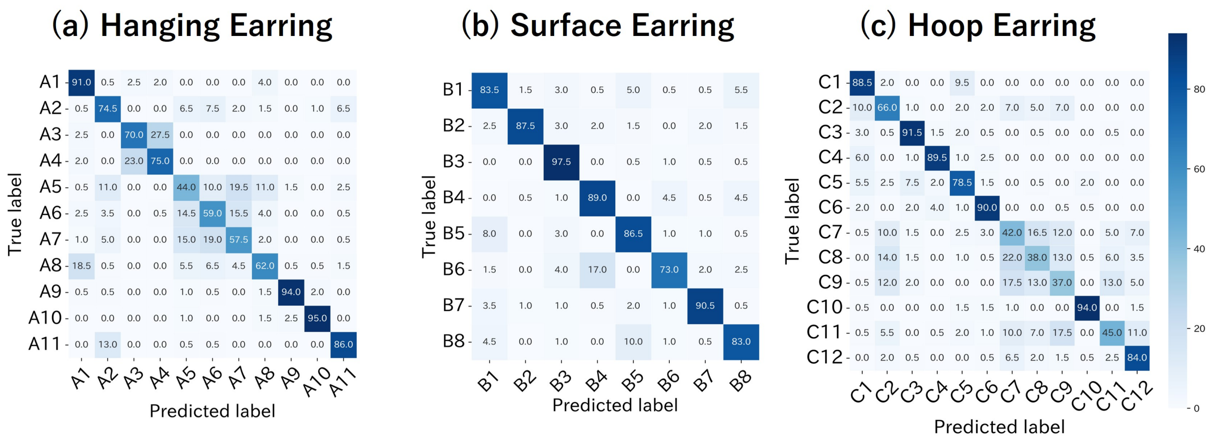

Fig. 7. Confusion Matrix in the between-individual model in each earring.

B. User Dependency

The mean accuracy of the between-individual model was 73.6% for hanging earrings, 84.4% for surface earrings, and 69.3% for hoop earrings. The accuracy of all earrings was worse than that of the within-individual model. This is likely due to differences in how individuals perform gestures. The more the gestures are different among users, the more difficult it is to identify them based on other people's training data.

Among the three earrings, the surface earring showed the smallest difference in accuracy between the within- and between-individual models. All gestures in the surface earring were gestures to touch the surface of the earring, indicating that the gestures to touch the surface of the fixation were highly reproducible.

The next smallest difference in accuracy was observed for the hanging earring. From Figures 6 and 7, we can see that the accuracy of the flicking gesture and the moving gesture decreased. It is thought that there were individual differences in the strength of the flicking and the precise direction of movement of the sphere.

C. Gesture Detection

In the user experiments in this study, participants performed gestures while seated and stationary. Gesture detection is an issue for future work. The hanging earring device did not implement gesture detection, and gesture recording started automatically. In the future, it is necessary to implement automatic gesture detection to identify gestures in real-time with hanging earrings. Since walking while wearing the hanging earrings causes the spherical part to sway, future work includes implementing a system that distinguishes between swaying caused by gestures and swaying caused by everyday movements such as walking.

On the other hand, the surface and hoop earrings implement gesture detection by comparing the sensor values before and after. For the surface earrings, gestures were detected by the proximity of a finger to the earring surface. For the hoop earrings, gestures were detected by skin contact with the capacitance sheet. Future research is needed to investigate whether unintended contact or proximity to the earring during daily movements may cause false gesture detection.

D. Improved Appearance

In addition to practicality, the natural appearance of the device is an important issue. The device created in this experiment acquires sensor values using wired communication. In practical use, the wiring will spoil the fashionable appearance of the device, so we will consider wireless communication. In the hanging earring, the 9-axis sensor was mounted externally on a commercially available earring, but we believe that its appearance can be improved by incorporating a sensor. The size of the device is also an important factor. It is important to keep the size of the device close to that of a normal earring to pursue a more natural device.

E. Variety of Earring Designs

In this study, we performed gesture exploration and gesture identification experiments on three commonplace earring shapes. While this study will be a precursor to earring devices, other shapes of earrings have not been studied. Future work should include gesture elicitation studies on earrings with more diverse shapes and characteristics. Future research should classify various types of earrings by investigating how their shapes and characteristics relate to intuitive, user-friendly gesture designs and validate the potential of using earrings as a gesture input interface.

VII. Conclusion

In this paper, we developed user-defined gesture sets for three types of earrings. Then, we also implemented earring devices to identify these gestures. The number of gesture sets was 11, 8, and 12 for each earring, and the average gesture identification accuracies for the within-individual models were 83.6%, 96.6%, and 87.0%, respectively. For the between-individual models, the mean accuracy for each earring was 73.6%, 84.4%, and 69.3%. In the future, we will pursue the natural appearance of the device to realize a fashionable and socially acceptable user interface.

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