2025 IEEE/SICE International Symposium on System Integration (SII)
January 21-24, 2025, Munich, Germany

SkinRing: Ring-shaped Device Enabling Wear Direction-Independent Gesture Input on Side of Finger

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***Abstract*— Ring-shaped devices are small, socially acceptable wearable devices that are gaining attention as health tracking and input devices. Although various ring-shaped input devices have been developed, they are limited in the direction of rotation when worn, requiring the user to be aware of the wear direction while wearing or operating the device. We propose the SkinRing, a ring-shaped device that enables gesture input on the side of the finger, regardless of the wear direction. The SkinRing consists of eight photo-reflective sensors attached to a ring, which is put on the index finger and acquires skin deformation information for gesture identification when the thumb touches the side of the index finger. The initial calibration of the hand's opening and closing allows for input independent of the direction of rotation of the ring when worn. A user study, where the identification results of nine gestures were given, shows an average accuracy of 87.8%.**

I. INTRODUCTION

Rings are prevalent accessories that have been extensively researched for interactive functionalities. Because of their small size and social acceptability, rings have attracted attention for use as input devices, and various ring-shaped input devices have been developed. Yet, due to their ring-shaped form factor, the input space is often limited to one-dimensional input [1], [2]. To expand this input capacity, previous studies have utilized the surrounding skin area [3], [4]. For instance, EFRing [3] harnesses electric field sensing to facilitate two-dimensional gesture input on the adjacent skin. FingerSound [4] uses a contact microphone and a gyroscope sensor to enable two-dimensional gesture input on the palm of the hand. Furthermore, users of ring-shaped devices often need to ensure the device's correct positioning on their finger to maintain accurate input coordinates. This makes it difficult to operate the device when users cannot see the hand and cannot reposition the device. Therefore, in order to improve the usability of the ring-shaped device, it is effective to enable input independent of wear direction and to eliminate the need to adjust the direction of rotation of the ring when wearing it.

We propose the SkinRing, a ring-shaped device that enables gesture input on the side of the finger independent of wear direction (Figure 1 (c)). The SkinRing consists of eight photo-reflective sensors attached to a ring that irradiates infrared light onto the finger. Photo-reflective sensors are mounted at equal intervals around the ring to ensure that, through calibration, input is independent of wear direction of rotation. Therefore, the SkinRing always allows input on the same plane even when the ring is rotated, enabling intuitive, eyes-free input. Moreover, the SkinRing allows for thumb gestures by tracing the skin of the index finger. This provides tactile feedback to both fingers, which is necessary for eyes-free input. With the SkinRing, you can even input with your hands down (Figure 1 (d)).

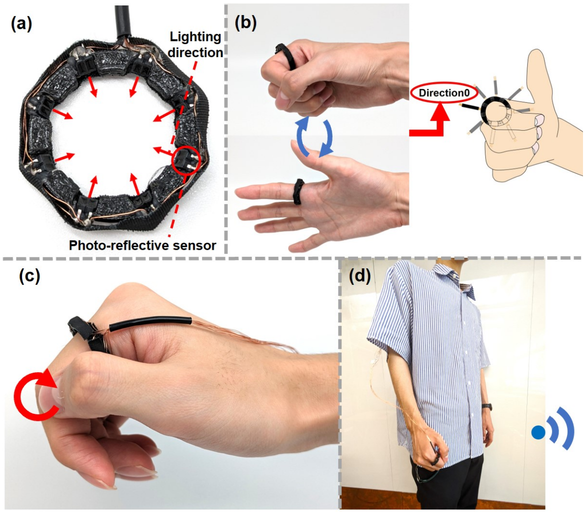

Fig. 1. (a) Direction of infrared radiation. (b) Calibration movement of hand's opening and closing. (c) SkinRing detects gesture input when the thumb touches the index finger. (d) Input with your hands down.

In this study, two levels of identification are used: the first is identification of the wear direction of ring rotation in which the ring is worn, and the second is gesture identification. We extracted features from the time-series data of skin deformation when the hand is opened and closed and identified the wear direction of ring rotation with random forest classification. Then, we extracted features from the time-series data of skin deformation when the thumb touched the index finger and identified the gestures with random forest classification also using the result of the identification of the wear direction. A user study, where the identification results of nine different gestures were given, revealed an average accuracy of 87.8% for gestures in eight different wear directions of rotation with calibration. This indicates that gesture input independent of wear direction of ring rotation is sufficiently feasible and therefore contributes to promoting comfortable and convenient input methods.

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II. RELATED WORK

A. Ring-shaped Input Devices

A lot of hand-based input methods have been studied, which allow humans to make minute movements. These include two main types of devices: wristband-type devices worn on the wrist [5], [6], [7] and ring-shaped devices worn on the finger [8], [9], [10], [11], [12], [13], [14], [2], [15], [3], [4]. These wristband-type devices have the advantage of being able to identify gestures using the entire hand, but they also have the disadvantage that the devices are large and conspicuous. In contrast, ring-shaped devices are smaller devices that can identify gestures.

Many ring-shaped input devices have been studied. These devices include those that allow input by directly touching the ring [12], [13], by touching a flat surface or other object [8], [13], by estimating hand posture [9], [10], and by using air gestures [11], [13].

Many studies also use the skin itself as an input surface. These studies have the advantage of using the skin surface as an interface to provide tactile feedback. For example, OptiRing [14] used low-resolution camera-based sensing to enable thumb-to-index finger gesture input, such as stateful pinch, swipes, and continuous one-degree-of-freedom input. Waghmare et al. [2] used active electrical field sensing and changes in the electrical impedance of the hand to enable various functions, including one-dimensional gesture input and user identification. Zhang et al. [15] enabled one-dimensional gestures of the thumb on each of the other fingers using an inertial measurement unit and a contact microphone. There are also devices that specifically enable two-dimensional gesture input. These include EFRing [3], which enables two-dimensional gesture input using electric field sensing. Zhang et al. [4] enabled two-dimensional gesture input with the palm of the hand using a contact microphone and a gyro sensor.

However, these devices that enable two-dimensional gesture input have limitations concerning the direction of rotation of the ring, requiring users to be cautious while wearing them. In this study, we propose a method to overcome this limitation by implementing calibration techniques, which allows for input independent of the direction of ring rotation and a more user-friendly experience.

B. Skin Deformation Detection

There are several studies that use photo-reflective sensors to detect skin deformations on body parts other than the finger. Some interface with ears [16], or cheeks [17], while others recognize facial expressions using earrings [18], glasses [19], and masks [20] through skin deformations. Some studies have also incorporated skin deformation into input methods using hands, which are capable of minute movements. Kitamura et al. [21] proposed a fingernail-type device that uses skin deformation of fingertips to identify micro gestures drawn on the index finger with the thumb. Ogata et al. [22], [23], [24] developed a wristwatch-type gesture input device using skin deformation of the wrist. They also proposed an input method that is performed by wearing a band-type device and moving the skin with the finger. Furthermore, they proposed a method to detect external pressure and finger rotation through a ring-shaped device.

However, the possibility of gesture identification with this ring-shaped device [24] has not been mentioned. In this study, a wide range of practicalities is considered by measuring the accuracy of gesture identification using a ring-shaped device that detects skin deformation.

III. SKINRING

We first explain the principle of skin deformation detection and then present the hardware we used. Finally, we describe in detail the identification system, including the calibration and gesture identification methods used.

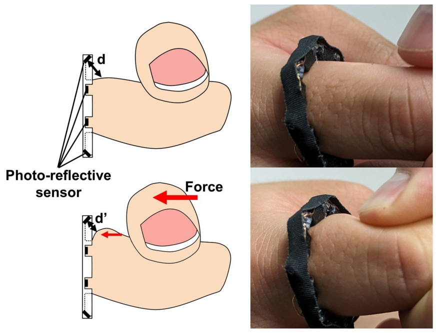

Fig. 2. Photo-reflective sensors detect skin deformation.

A. Principle of Skin Deformation Detection

In this study, photo-reflective sensors are used to detect skin deformation. A photo-reflective sensor emits infrared light from a light-emitting element and detects the reflected light with a light-receiving element. The amount of reflected light varies depending on the distance between the object and the sensor, allowing the distance to be measured. When the hand is opened or closed, or when the thumb traces the side of the index finger, the skin near the ring undergoes deformation. The skin deformation is detected by measuring the distance between the photo-reflective sensor and the skin of the finger, as shown in Figure 2, and the sensor values are used to calibrate the direction of rotation of the ring and identify gestures.

B. Hardware Design

The device made in this study is shown in Figure 1 (a). Eight photo-reflective sensors (SG-105: Kodenshi Corp.) are attached to a ring made by a 3D printer. Based on symmetry, the number of sensors was considered to be four or 16, but eight was chosen for this study because four sensors do not provide sufficient identification accuracy and there is not enough space on the ring to attach 16 sensors. These sensors emit infrared light to the finger. We measured the finger sizes of the experiment participants and then made two types of devices to fit the participants' finger sizes: a large size and a small size. The diameter of the large size is 21 mm, and

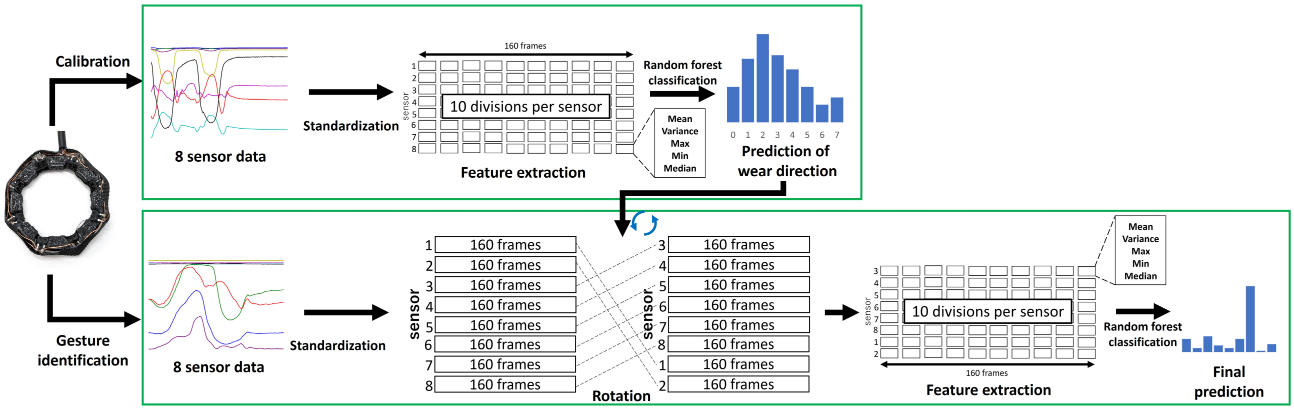

Fig. 3. Calibration and gesture identification.

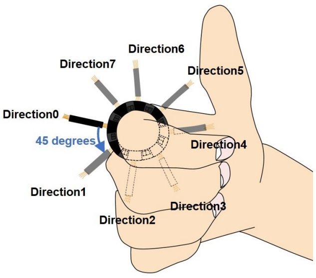

Fig. 4. Directions of ring rotation.

the diameter of the small size is 19 mm. The sensor values acquired from the photo-reflective sensors are transmitted to a laptop (ASUS: Zenbook 14) using an Arduino Pro Mini 3.3V. The sampling rate is approximately 80 fps.

C. Identification System

In this system, the wear direction of rotation of the ring is initially predicted by calibration, and the predicted direction of rotation is used in subsequent gesture identification to enable gesture identification in any direction of rotation of the ring.

1) Calibration: The purpose of calibration is to identify the direction of rotation in which the ring is worn. In this study, the hand is opened and closed twice from the closed state as a calibration (Figure 1 (b)). Before gesturing, calibration movement is performed and eight sensor values of 160 frames each are acquired. After standardizing the time-series data, each sensor data is divided into 10 parts in time-series order (with 16-frame intervals), and five features (mean, variance, maximum, minimum, and median) are extracted for each part. The direction of rotation is then predicted with a random forest (upper side of Figure 3). Based on this prediction, the eight sensor gesture data is reordered to reduce the effect of rotation of the ring and enable gesture identification independent of wear direction of rotation.

2) Gesture Identification: After calibration, eight sensor values of 160 frames each are obtained as gesture data, and the order of the sensor data is rearranged to match the wear direction of rotation predicted by the calibration after standardization. Then, each sensor data is divided into 10 parts in time-series order (with 16-frame intervals), and five features are extracted for each part just as in the calibration process. Finally, the gesture is predicted with a random forest (lower side of Figure 3).

Since the calibration process can only identify eight discrete wear directions of rotation, it cannot predict the exact wear direction. Therefore, in the gesture identification experiment in eight wear directions (Figure 4) shown in Section IV-C, we used not only the sensor data reordered to the actual wear direction as training data at the time of evaluation, but also the sensor data reordered to the two adjacent wear directions: forward and backward. In the identification of test data, in addition to the predicted probabilities for the sensor data reordered to the wear direction predicted by the calibration model, the predicted probabilities for the sensor data reordered to the two adjacent wear directions were calculated. Then the gesture with the highest probability among all was chosen (Figure 5). We confirmed that this method improves the accuracy of gesture identification. The random forest classifier was created using the python scikit-learn library.

IV. EVALUATION

A user study was conducted on 10 participants to measure the identification accuracy of the SkinRing. There were eight male and two female participants (mean age 23.3 years, standard deviation 2.34 years), all of whom were right-handed. The ring used varied between small and large sizes according to the size of the user's finger. Three participants used the large size, and seven participants used the small size. Participants wore the SkinRing on the index finger of their right hand in the experiments. All experiments were conducted indoors. All experiments were approved for ethics application at the author's home institution (ethics review number: 2023-090).

A. Experiment 1: Gesture with Ring in One Wear Direction

1) Overview: In this experiment, as a baseline study, we evaluated the gesture identification accuracy when participants wore the SkinRing in one wear direction of ring

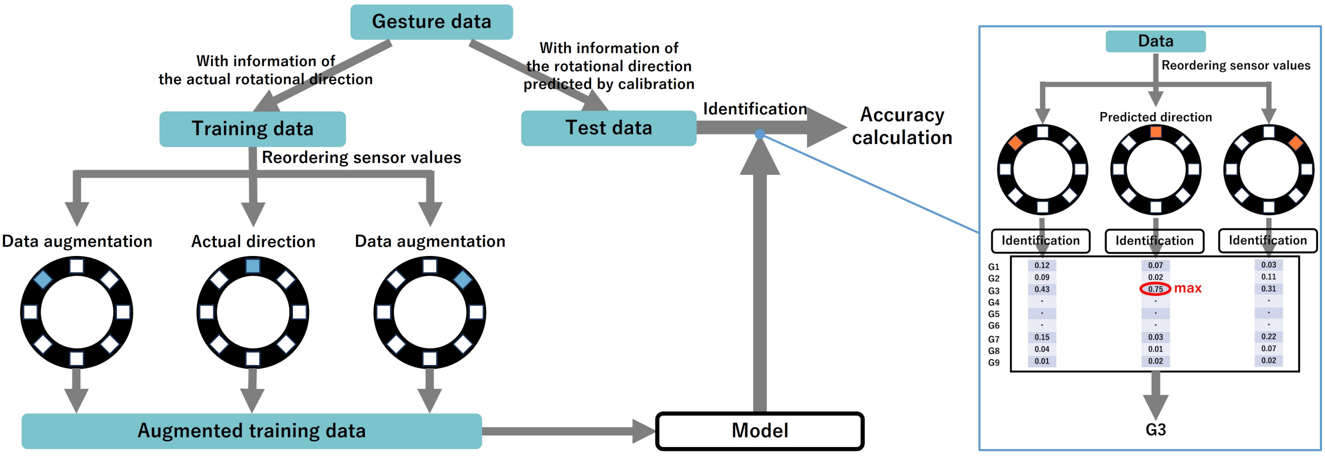

Fig. 5. Identification method.

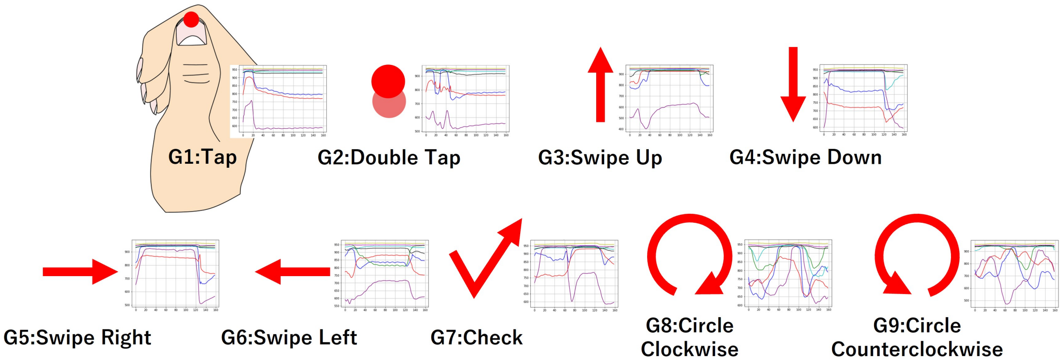

Fig. 6. Gesture set.

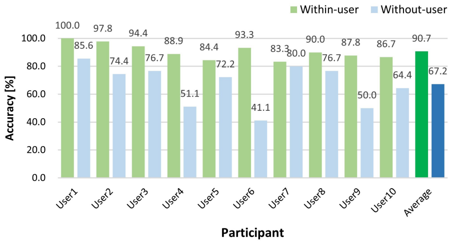

Fig. 7. Gesture identification accuracy in one wear direction.

rotation. We fixed the direction of rotation of the ring in Direction0 with the wire pointing toward the back of the hand, as shown in Figure 4, and a total of nine gestures shown in Figure 6 were used to evaluate identification accuracy. The gesture set used was from a previous study on ring-based gestures [3]. Before the experiment, participants practiced all gestures. In the experiment, one set consisted of performing all nine gestures one time each, and participants performed 10 sets of this. The ring was taken off and put back on again after each set.

2) Results: We performed within-user and without-user cross-validation on the 10 sets of sensor data acquired. In within-user cross-validation, one set of gesture data was used as test data and the remaining nine sets of gesture data were used as training data for each individual, and in without-user cross-validation, one person's gesture data was used as test data and the remaining nine people's gesture data were used as training data. As a result, the average within-user identification accuracy of nine gestures was 90.7% and the average without-user identification accuracy of nine gestures was 67.2%. The within-user and without-user identification accuracy for each user are shown in Figure 7. These results indicate that without-user identification is much more difficult than within-user identification. This may be due to the individual differences in finger size and gesture style. It is difficult to unify skin movements among individuals because skin moving gestures are not common, and this method requires that a model be trained for each individual.

B. Experiment 2: Calibration of Wear Direction

1) Overview: This experiment evaluated the identification accuracy of the wear direction of ring rotation predicted by the calibration of the hand's opening and closing twice shown in Figure 1 (b). Participants performed the calibration movement three times for each of the eight wear directions of ring rotation shown in Figure 4. The angular interval in each direction is 45 degrees. In Direction0, the wire points

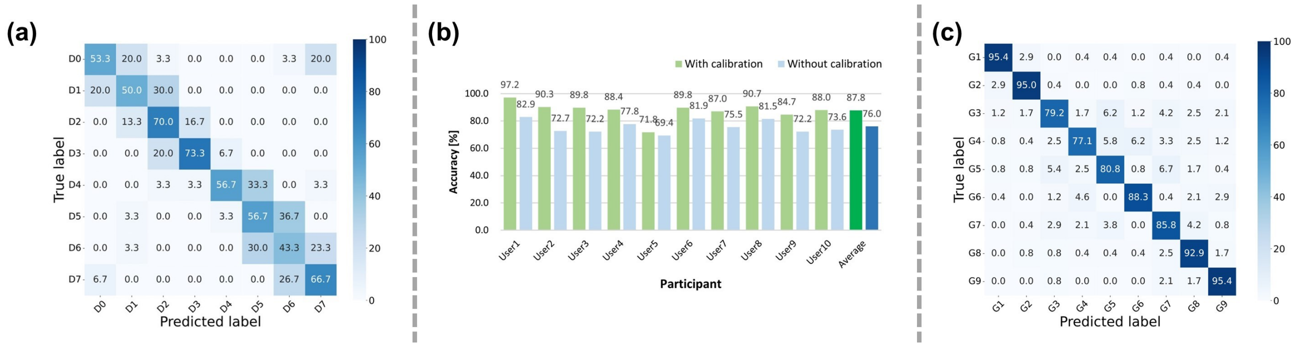

Fig. 8. (a) Identification accuracy of the direction of rotation. (b) Gesture identification accuracy in eight wear directions. (c) Identification accuracy of nine gestures.

toward the back of the hand. The ring was taken off and put back on again each time.

2) Results: We performed within-user cross-validation on the acquired sensor data. One time calibration data for one direction was used as test data, and calibration data other than the test data were used as training data. As a result, the average identification accuracy of eight wear directions was 58.8%. The confusion matrix is shown in Figure 8 (a). The average distance error, which is the average distance between the predicted label and the correct label when the distance between the label and the adjacent label is set to 1 for each wear direction, was 0.413. The average identification accuracy was 99.2% when not only the actual correct label but also the both neighboring labels were considered as correct labels. These results and the confusion matrix reveal that calibration cannot accurately determine the direction of rotation, but it can make a prediction including the adjacent direction-of-rotation labels, with a probability of almost 100%. The adjacent wear directions are easily misidentified, and gesture identification should take into account the possibility that the gesture is in the wear direction next to the wear direction predicted by calibration.

C. Experiment 3: Gesture with Ring in Eight Wear Directions

1) Overview: This experiment evaluated the gesture identification accuracy when participants wore the SkinRing in the eight wear directions shown in Figure 4. Since the gestures in Direction0 were recorded in Experiment 1 in Section IV-A, participants performed three sets of gestures in each of the remaining seven wear directions. One set consisted of performing all nine gestures shown in Figure 6 one time each, and the ring was taken off and put back on again after each set.

2) Results: We performed within-user cross-validation on the three sets of sensor data for the eight wear directions with and without calibration for each user. One set of gesture data for one direction was used as test data and gesture data other than the test data were used as training data. The calibration model used was the within-user model created from the data obtained in Experiment 2 in Section IV-B. The results showed that the average identification accuracy of nine gestures was 87.8% with calibration and 76.0% without calibration. The identification accuracy with and without calibration for each user are shown in Figure 8 (b), and the confusion matrix of gesture identification accuracy with calibration is shown in Figure 8 (c). Regarding the gestures, it was observed that mistakes were easily made, especially among the swipes (G3-G6) and check (G7) gestures. These simple straight line gestures are more difficult to identify than other gestures because the gesture times are comparable and the increase or decrease in sensor values caused by the skin moving in various directions is less characteristic in these gestures.

The experimental results show that calibration facilitates gesture identification independent of the direction of rotation of the ring, as can be seen in the individual results. Considering the actual use of the device by users, it would be a significant effort to perform 10 sets of all gestures in eight wear directions in order to achieve the 90.7% identification accuracy, which is the average identification accuracy of 10 sets of gestures in one wear direction. Therefore, the fact that 87.8% accuracy was achieved with only three sets of trials is a major contribution of this study.

V. LIMITATIONS AND FUTURE WORK

A. Limitations

In this study, we proposed a method to enable input independent of the direction in which a ring-shaped device is worn. However, the proposed SkinRing has several limitations. First, the usability of the device varies depending on individual differences. Photo-reflective sensors emit infrared light and measure the intensity of the reflected light, thus the sensitivity of the sensors varies depending on the skin color and individual features of the user's skin surface. Furthermore, because the size of the ring is fixed, the sensor values vary depending on the thickness of the individual's fingers. In addition, the sensor values vary for the same person depending on the degree of fingers swelling on any given day. Therefore, in the future, it is necessary to calibrate the initial sensor values with the ring on and to adjust the sensitivity of sensors in addition to the calibration of the wear direction of the ring. It is also important to ensure that the ring matches the thickness of an individual's finger when it is actually used as a product.

Another issue is that it takes time to learn the gestures to move the skin. Some participants found it difficult to perform the gesture using skin deformation. Some participants also said that their fingers hit the ring when they gestured, thus we need to consider the gesture position.

Moreover, although the experiment was conducted indoors, the SkinRing is affected by infrared rays contained in ambient light, which limits its use in places with strong sunlight. To solve this problem, it is necessary to shut out other light coming toward the photo-reflective sensors. This requires changes in the shape of the device.

B. Future Work

In this study, the three experiments were conducted consecutively with breaks, resulting in a long experiment and not enough data per participant. In addition, the participants were currently limited to young people. Therefore, we plan to increase the number of participants and the amount of data acquired in the future. Although only two sizes of devices were used in this study, it will be necessary to use more sizes of devices, because in practice, more suitable devices should be provided to each user. Furthermore, if smaller photo-reflective sensors than those used in this study are used, 16 of them could be attached to the device, and higher gesture identification accuracy might be achieved.

Evaluation experiments have confirmed that the proposed device is capable of gesture identification in a laboratory environment. On the other hand, the without-user identification accuracy is significantly degraded, and it is necessary to construct a dataset for each user in the current situation. This is thought to be due to the individual differences mentioned in the limitations. As a solution, transfer learning in a pre-trained deep learning model as shown in the study by Kikui et al. [25] has the potential to improve the identification accuracy constructing a small dataset for each user to use the device.

In this study, we used random forest for gesture identification, but there are various other algorithms (Support Vector Machine, Recurrent Neural Network, etc.). These other methods should be tested in the future.

For practical use, a lock function should be added to prevent users from unintended input while wearing the ring. Furthermore, although this study only mentions the possibility of wearing the SkinRing on the index finger, it is also possible to wear it on the middle finger due to the large gesture area on the skin and the user's comfort during gestures. The possibility of wearing the device on multiple fingers would expand the use scenarios, such as when a specific finger is injured. If the SkinRing can be used not only for gesture identification but also for pointing operation, the range of practical uses will be further expanded. We would also like to prove its practicality by developing applications for operations in VR that require eyes-free input, and for visually impaired people for whom it is difficult to take into account the direction of rotation of the ring. We believe that the ultimate goal is to enable more comfortable input by making the device wireless.

VI. CONCLUSION

In this paper, we propose the SkinRing, a ring-shaped device that enables gesture input on the side of the finger independent of wear direction of rotation. The average identification accuracy of nine different gestures was 87.8%. We believe that this study contributed to the advancement of ring-shaped input devices, as we found the advantage of being able to ignore the direction of rotation when wearing the ring-shaped device. The ring-shaped device which is independent of wear direction of rotation enables eyes-free input at any time unlike conventional ring-shaped devices. In the future, we will work on increasing the ring size, pursuing the possibility of wearing the device on the middle finger, and implementing pointing operations in order to improve the versatility of the device. At the same time, for practical use, we will try to add a lock function to prevent malfunction when the ring is worn and to promote comfortable input by making the device wireless.

The ring-shaped device which is independent of wear direction of rotation enables eyes-free input at any time unlike conventional ring-shaped devices.

ACKNOWLEDGMENT

Part of this work was supported by JSPS KAKENHI (grant numberJP21H03485). Part of this work was supported by JST PRESTO (Grant Number JPMJPR2134).

REFERENCES

[1] D. Ashbrook, P. Baudisch, and S. White, “Nenya: Subtle and eyes-free mobile input with a magnetically-tracked finger ring,” in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, ser. CHI '11. New York, NY, USA: Association for Computing Machinery, 2011, p. 2043–2046. [Online]. Available: https://doi.org/10.1145/1978942.1979238

[2] A. Waghmare, Y. Ben Taleb, I. Chatterjee, A. Narendra, and S. Patel, “Z-ring: Single-point bio-impedance sensing for gesture, touch, object and user recognition,” in *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, ser. CHI '23. New York, NY, USA: Association for Computing Machinery, 2023. [Online]. Available: https://doi.org/10.1145/3544548.3581422

[3] T. Chen, T. Li, X. Yang, and K. Zhu, “Efring: Enabling thumb-to-index-finger microgesture interaction through electric field sensing using single smart ring,” *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, vol. 6, no. 4, jan 2023. [Online]. Available: https://doi.org/10.1145/3569478

[4] C. Zhang, A. Waghmare, P. Kundra, Y. Pu, S. Gilliland, T. Ploetz, T. E. Starner, O. T. Inan, and G. D. Abowd, “Fingersound: Recognizing unistroke thumb gestures using a ring,” *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, vol. 1, no. 3, sep 2017. [Online]. Available: https://doi.org/10.1145/3130985

[5] J. Gong, X.-D. Yang, and P. Irani, “Wristwhirl: One-handed continuous smartwatch input using wrist gestures,” in *Proceedings of the 29th Annual Symposium on User Interface Software and Technology*, ser. UIST '16. New York, NY, USA: Association for Computing Machinery, 2016, p. 861–872. [Online]. Available: https://doi.org/10.1145/2984511.2984563

[6] R. Fukui, M. Watanabe, T. Gyota, M. Shimosaka, and T. Sato, “Hand shape classification with a wrist contour sensor: development of a prototype device,” in *Proceedings of the 13th International Conference on Ubiquitous Computing*, ser. UbiComp '11. New York, NY, USA: Association for Computing Machinery, 2011, p. 311–314. [Online]. Available: https://doi.org/10.1145/2030112.2030154

[7] J. McIntosh, A. Marzo, and M. Fraser, “Sensir: Detecting hand gestures with a wearable bracelet using infrared transmission and reflection,” in *Proceedings of the 30th Annual ACM Symposium on User Interface Software and Technology*, ser. UIST ’17. New York, NY, USA: Association for Computing Machinery, 2017, p. 593–597. [Online]. Available: https://doi.org/10.1145/3126594.3126604

[8] W. Kienzle and K. Hinckley, “Lightring: Always-available 2d input on any surface,” in *Proceedings of the 27th Annual ACM Symposium on User Interface Software and Technology*, ser. UIST ’14. New York, NY, USA: Association for Computing Machinery, 2014, p. 157–160. [Online]. Available: https://doi.org/10.1145/2642918.2647376

[9] W. Sun, F. M. Li, C. Huang, Z. Lei, B. Steeper, S. Tao, F. Tian, and C. Zhang, “Thumbtrak: Recognizing micro-finger poses using a ring with proximity sensing,” in *Proceedings of the 23rd International Conference on Mobile Human-Computer Interaction*, ser. MobileHCI ’21. New York, NY, USA: Association for Computing Machinery, 2021. [Online]. Available: https://doi.org/10.1145/3447526.3472060

[10] A. Waghmare, I. Chatterjee, and S. Patel, “Z-pose: Continuous 3d hand pose tracking using single-point bio-impedance sensing on a ring,” in *Proceedings of the 2nd Workshop on Smart Wearable Systems and Applications*, ser. SmartWear ’23. New York, NY, USA: Association for Computing Machinery, 2023, p. 1–6. [Online]. Available: https://doi.org/10.1145/3615592.3616851

[11] H. Kokubu, K. Tominaga, and B. Shizuki, “One–handed control for smartwatches using thumb gestures to ring,” in *Proceedings of the Asian HCI Symposium 2022*, ser. Asian HCI ’22. New York, NY, USA: Association for Computing Machinery, 2023, p. 30–32. [Online]. Available: https://doi.org/10.1145/3516492.3558790

[12] J. Kim, W. Delamare, and P. Irani, “Thumbtext: Text entry for wearable devices using a miniature ring,” in *Proceedings of the 44th Graphics Interface Conference*, ser. GI ’18. Waterloo, CAN: Canadian Human-Computer Communications Society, 2018, p. 18–25. [Online]. Available: https://doi.org/10.20380/GI2018.04

[13] S. Bardot, S. Rawat, D. T. Nguyen, S. Rempel, H. Zheng, B. Rey, J. Li, K. Fan, D.-Y. Huang, W. Li, and P. Irani, “Aro: Exploring the design of smart-ring interactions for encumbered hands,” in *Proceedings of the 23rd International Conference on Mobile Human-Computer Interaction*, ser. MobileHCI ’21. New York, NY, USA: Association for Computing Machinery, 2021. [Online]. Available: https://doi.org/10.1145/3447526.3472037

[14] A. Waghmare, R. Boldu, E. Whitmire, and W. Kienzle, “Optiring: Low-resolution optical sensing for subtle thumb-to-index micro-interactions,” in *Proceedings of the 2023 ACM Symposium on Spatial User Interaction*, ser. SUI ’23. New York, NY, USA: Association for Computing Machinery, 2023. [Online]. Available: https://doi.org/10.1145/3607822.3614538

[15] C. Zhang, X. Wang, A. Waghmare, S. Jain, T. Ploetz, O. T. Inan, T. E. Starner, and G. D. Abowd, “Fingorbits: Interaction with wearables using synchronized thumb movements,” in *Proceedings of the 2017 ACM International Symposium on Wearable Computers*, ser. ISWC ’17. New York, NY, USA: Association for Computing Machinery, 2017, p. 62–65. [Online]. Available: https://doi.org/10.1145/3123021.3123041

[16] T. Kikuchi, Y. Sugiura, K. Masai, M. Sugimoto, and B. H. Thomas, “Eartouch: Turning the ear into an input surface,” in *Proceedings of the 19th International Conference on Human-Computer Interaction with Mobile Devices and Services*, ser. MobileHCI ’17. New York, NY, USA: Association for Computing Machinery, 2017. [Online]. Available: https://doi.org/10.1145/3098279.3098538

[17] K. Yamashita, T. Kikuchi, K. Masai, M. Sugimoto, B. H. Thomas, and Y. Sugiura, “Cheekinput: Turning your cheek into an input surface by embedded optical sensors on a head-mounted display,” in *Proceedings of the 23rd ACM Symposium on Virtual Reality Software and Technology*, ser. VRST ’17. New York, NY, USA: Association for Computing Machinery, 2017. [Online]. Available: https://doi.org/10.1145/3139131.3139146

[18] K. Futami, K. Oyama, and K. Murao, “Augmenting ear accessories for facial gesture input using infrared distance sensor array,” *Electronics*, vol. 11, no. 9, 2022. [Online]. Available: https://www.mdpi.com/2079-9292/11/9/1480

[19] K. Masai, Y. Sugiura, M. Ogata, K. Kunze, M. Inami, and M. Sugimoto, “Facial expression recognition in daily life by embedded photo reflective sensors on smart eyewear,” in *Proceedings of the 21st International Conference on Intelligent User Interfaces*, ser. IUI ’16. New York, NY, USA: Association for Computing Machinery, 2016, p. 317–326. [Online]. Available: https://doi.org/10.1145/2856767.2856770

[20] H. Lee, Y. Kim, and A. Bianchi, “Mascreen: Augmenting speech with visual cues of lip motions, facial expressions, and text using a wearable display,” in *SIGGRAPH Asia 2020 Emerging Technologies*, ser. SA ’20. New York, NY, USA: Association for Computing Machinery, 2020. [Online]. Available: https://doi.org/10.1145/3415255.3422886

[21] R. Kitamura, T. Yamamoto, and Y. Sugiura, “Touchlog: Finger micro gesture recognition using photo-reflective sensors,” in *Proceedings of the 2023 ACM International Symposium on Wearable Computers*, ser. ISWC ’23. New York, NY, USA: Association for Computing Machinery, 2023, p. 92–97. [Online]. Available: https://doi.org/10.1145/3594738.3611371

[22] M. Ogata and M. Imai, “Skinwatch: Skin gesture interaction for smart watch,” in *Proceedings of the 6th Augmented Human International Conference*, ser. AH ’15. New York, NY, USA: Association for Computing Machinery, 2015, p. 21–24. [Online]. Available: https://doi.org/10.1145/2735711.2735830

[23] M. Ogata, Y. Sugiura, Y. Makino, M. Inami, and M. Imai, “Senskin: Adapting skin as a soft interface,” in *Proceedings of the 26th Annual ACM Symposium on User Interface Software and Technology*, ser. UIST ’13. New York, NY, USA: Association for Computing Machinery, 2013, p. 539–544. [Online]. Available: https://doi.org/10.1145/2501988.2502039

[24] M. Ogata, Y. Sugiura, H. Osawa, and M. Imai, “Iring: Intelligent ring using infrared reflection,” in *Proceedings of the 25th Annual ACM Symposium on User Interface Software and Technology*, ser. UIST ’12. New York, NY, USA: Association for Computing Machinery, 2012, p. 131–136. [Online]. Available: https://doi.org/10.1145/2380116.2380135

[25] K. Kikui, Y. Itoh, M. Yamada, Y. Sugiura, and M. Sugimoto, “Intra-/inter-user adaptation framework for wearable gesture sensing device,” in *Proceedings of the 2018 ACM International Symposium on Wearable Computers*, ser. ISWC ’18. New York, NY, USA: Association for Computing Machinery, 2018, p. 21–24. [Online]. Available: https://doi.org/10.1145/3267242.3267256