Touch Position Detection on the Front of Face Using Passive High-Functional RFID Tag with Magnetic Sensor

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Abstract. We used passive, high-functional radiofrequency identification (RFID) tags with magnetic sensors to detect front of face touch positions without the requirement for a battery. We implemented a prototype system consisting of a goggle-type device equipped with passive high-functional RFID tags with magnetic sensor, a ring with permanent magnets, and touch detection software for machine-learning. We evaluated the classification accuracy of the six front of face touch positions and a 'no-touch' case. The discrimination rate when using the learning data was 83% but the real-time discrimination was only 65%. In future, we will aim to improve the accuracy, and define more touch points and gesture inputs.

Keywords: Magnetic sensing · RFID tag · Touch sensing

1 Introduction

Wearable devices are becoming increasingly common, as are gesture inputs. However, most gesture input methods require sensors or additional devices for classification, and a power supply. If power is delivered by wire, the useable space is reduced. A battery may explode or degrade at excessively high or low temperatures.

We developed a battery-free gesture input method for wearable devices; touch positions are detected using passive high-functional radiofrequency identification (RFID) tags with magnetic sensors; the microcomputer and sensors are powered by radio waves. RFID tags have been used to power e-ink displays and sense temperature [9], and for attendance management systems [8]. Here, we detect the touch positions using a goggle-type device equipped with passive, high-functional RFID tags featuring magnetic sensor and a ring with a permanent magnet. The user wears the goggles and the ring; when the face is touched with the ring-bearing finger, the touch position is classified; no other sensor is required. Face-touching is a natural behavior and touch positions can be defined easily.

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2 Related Work

In this section, we review 1) sensing methods and gesture inputs based on magnetism; 2) previous research on battery-free devices; and, 3) work on RFID technology.

2.1 Sensing Methods and Gesture Inputs based on Magnetism

Many input methods using magnetic sensors have been described. Abracatabra [4] described wireless power-free inputs for small devices (such as smart watches); the position of a finger with an attached magnet was detected. IM6D [5] uses a magnetic sensor array to measure the three-dimensional position and direction of a fingertip-mounted electromagnet. Finexus [1] tracks a fingertip-attached electromagnet in real time by evaluating the magnetic field using sensors strapped to the back of the hand.

2.2 Battery-Free Devices

Grosse-Puppendahl et al. [3] created a battery-free display using a solar cell, a Bluetooth low-energy (BLE) device, and electronic paper; the display provided reminders and weather data via a PC or smartphone. Li et al. [7] used low-cost photodiodes for both ambient lighting and gesture classification; the self-powered module was accurate under various ambient light conditions. Similarly, for our device, gestures are inputted using a battery-free goggles. However, our device is based on RFID technology and used magnetic sensors to detect face touch positions.

2.3 Input Methods Using RFID Technology

RFID is widely used for object and personal identification. Both power delivery and information exchange are achieved wirelessly. Tip-tap [6] collects data from the intersections of arrays attached to the thumb and forefinger to yield discrete two-dimensional touch inputs, without the requirement for a battery. Based on Near Field Communication (NFC; a type of RFID), NFC-WISP [9] is used to power electronic printing devices, temperature sensors and contactless tap cards. AlterWear [2] is a new battery-free wearable device based on electromagnetic induction via NFC; the display uses bistable electronic ink.

3 Examples

We explored how inputs may drive music applications and devices with small screens.

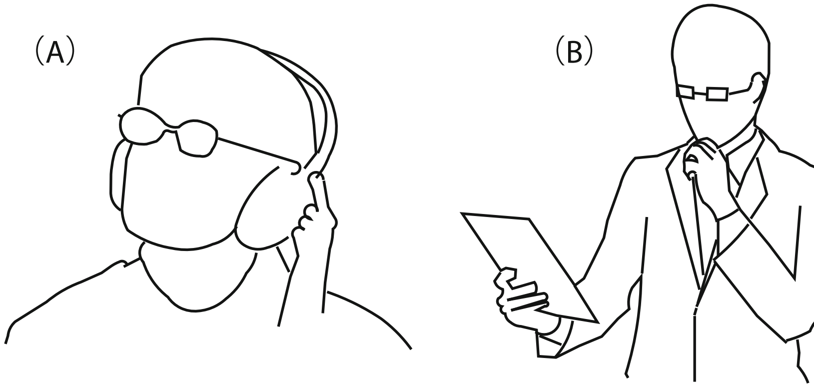

Fig. 1. (A) Inputs for music applications, (B) Character inputs for devices with small screens.

3.1 Music Applications

On crowded public transport, it can be difficult to operate a music player. However, using our method [Fig. 1(A)] the user can play or stop music by touching the ear, and control the volume by touching the mouth.

3.2 Devices with Small Screens

Character input using a small touch screen (such as that of a smart watch) is difficult. With our device, character inputs are mapped to facial regions [Fig. 1(B)] and characters are input using the fingertips.

4 Prototype

The prototype features a goggle-type device with passive, high-functional RFID tags with magnetic sensor; an RFID reader; a ring with a permanent magnet; and a touch position classifier running on a PC (Fig. 2).

4.1 The Goggle-Type Device and the RFID Reader

The goggle-type device comprises a pair of plastic goggles equipped with two passive, high-functional RFID tags with magnetic sensor (EVAL01-Magneto-RM; Farsens[1]) supported on either side by 3D-printed bars (Fig. 3). The tags were lie about 3.5 cm distant from goggles; reception is poor if the RFID is too close to the skin [6].

Our device uses an Impinj Speedway Revolution R420 RFID reader. The output is 32.5 dBm when power is supplied by an AC adapter. The reader is connected to a PC. We also used a YAP-102CP as the reader antenna.

[1] http://www.farsens.com/en/products/eval01-magnetorm/.

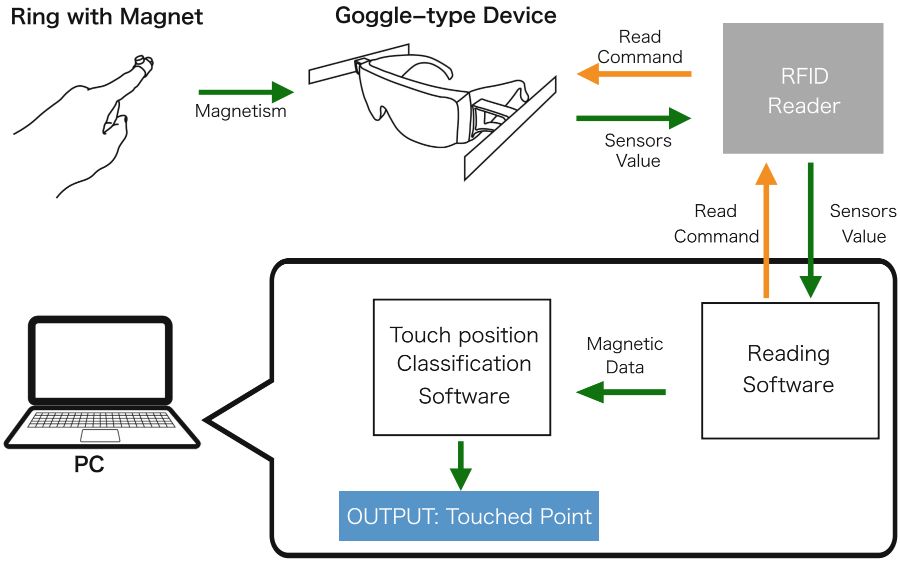

Fig. 2. Overview of the prototype.

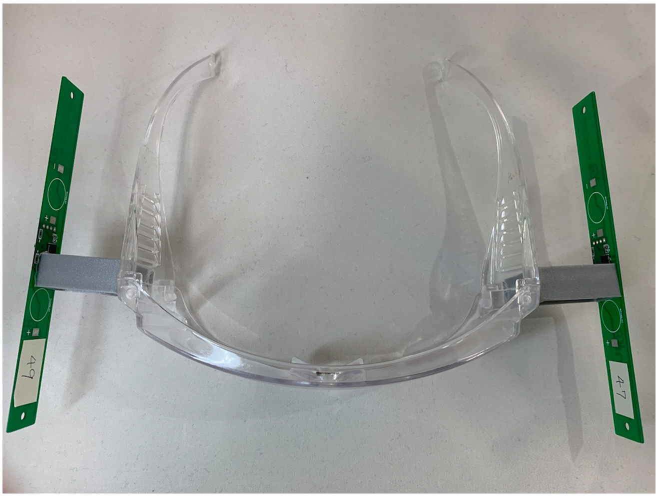

Fig. 3. The goggle-type device.

4.2 Ring with Permanent Magnets

Fig. 4. Rings with attached magnet.

The goggle-type device uses a magnetic sensor; a finger magnet is thus required. We devised two three-dimensional-printed rings differing in diameter, with notches for the magnets. Both rings had a gap at the bottom; they were thus suitable for fingers varying in size and shape (Fig. 4).

4.3 Touch Position Classifier

The touch position classifier uses a data collecting program written in Java, and a classifier written in Python. The data collection program first sends read commands to the RFID tags via RFID reader, and the tags send results to the software via the reader. Because the geomagnetism influences sensor output, we subtracted the median geometric value of 100 'no-touch' signals.

Sensor data from both of magnetic sensor tags ('one-frame' data) are then classified. To rule-out over-learning, a frame is discarded if it is identical to the previous frame. Each frame is classified as one of the predefined touch positions. The classification model employs the k-nearest-neighbor algorithm of the Python scikit-learn library. The hyperparameters, established via 5-fold cross-validation and grid searching, were as follows:

- Number of neighboring points: 7
- Weight: distance
- Distance: Manhattan

4.4 Sensor Data Reception

We evaluated the data reception rate with the RFID sensor tag or the goggle-type device placed on a wooden desk. The reader antenna was placed 22 cm above the desk and read three-axis magnetic sensor data. We quantified the data received over 5 s and calculated the reception rates as ∼20 Hz for a single RFID tag and 5–10 Hz for the goggle-type device (two tags). The reception rate for the goggle-type device allowed adequate classification of touch position, but the rate fluctuated and the two tags were not equidistant from the reader. In the future, we will resolve this problem by controlling the reader settings.

4.5 Effect of Magnets

We assessed whether the magnet affected the sensor using the setup described above. We put a set of two magnets (used for our ring device) on the desk 1, 2, 3, 4, 5, 10, 15, and 20 cm apart from the sensor. We collected 2,000 sets of data and calculated the median value (Fig. 5). The vertical axis shows the sensor data (three-axis magnetic vectors) minus the median geomagnetic vector (calculated using 2,000 sensor data points collected without magnets). The sensor detects magnets at a distance of 5–10 cm away from the sensor. Thus, the facial touchpoints should lie within about 10 cm of the sensor.

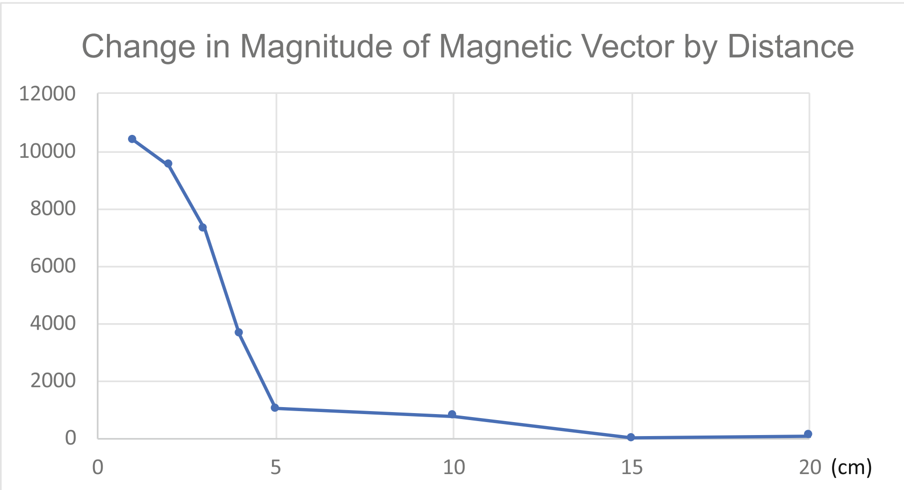

Fig. 5. Change in magnitude of magnetic vector by distance.

5 Evaluation

We evaluated facial touch accuracy in a single male subject who wore the goggle-type device and ring with a permanent magnet on the index finger of the right hand; the subject was in a sitting position.

5.1 Procedure

In the first learning phase, data were collected for machine-learning. In the classification phase, whether touch positions were accurately classified was determined.

In the first phase, 200 magnetic data frames were collected from each touch point (1,400 frames = 200 × 6 touch points + 200 'no-touch' cases). Figure 6 shows the six touch points. shows the position of the 7 touch points. The subject was asked to continuously rotate the index finger to prevent over-learning due to changes in finger angle. Then, 80% of the collected data were used for training; 20% were reserved for testing. We employed a k-nearest neighbor (KNN) machine-learning algorithm. We performed 5-fold cross-validation to improve performance generalization.

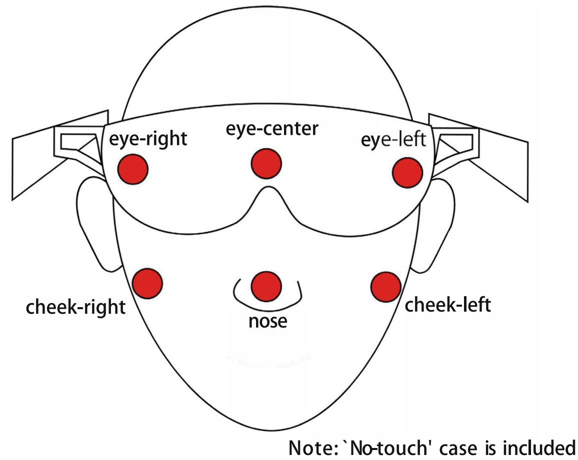

Fig. 6. The six touch points on the face.

During the classification phase, the subject touched each facial point 10 times and also performed 'no-touch' 10 times (total of 70 trials) in a random order. For each touch, the index finger remained in place until 10 data frames were collected; the median value was used for classfication. The results were recorded, displayed, and labeled, and the success rate was calculated.

5.2 Results and Discussion

The classification accuracy for the test data collected during the learning phase was 83%. However, for the 70 frames of magnetic data collected during the classification phase, the accuracy was only 65%. Figure 7 shows the classification confusion matrix. The classification accuracy for the test data collected during the learning phase was high. However, the classification accuracy was lower for the data collected during the classification phase. Two vertical points were often misclassfied, such as ‘eye-left’ and ‘cheek-left’. In the future, we will aim to improve the training model by adding other features. For example, when we added two magnitudes calculated from two magnetic vectors of the two sensor tags to the feature vectors, the classification accuracy improved slightly (Fig. 8).

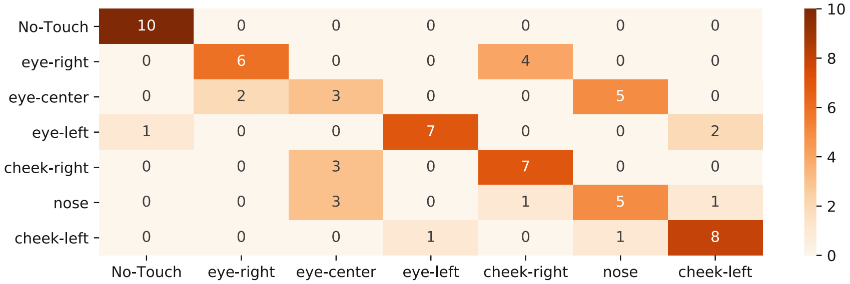

Fig. 7. Confusion matrix derived from 50 frames of test data classified by the KNN model. Only three-axis magnetic vectors of the two sensor tags were used as feature vectors.

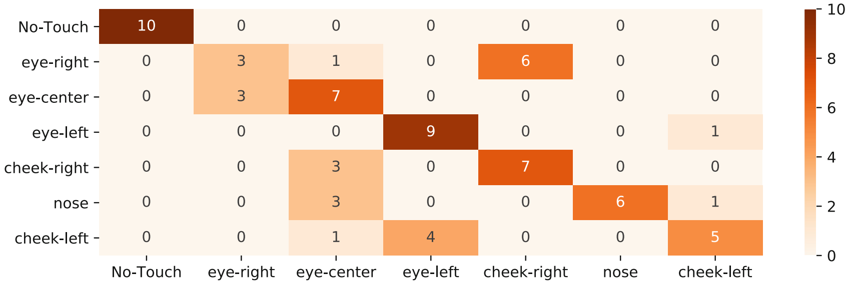

Fig. 8. Confusion matrix derived from 50 frames of test data were classified by the KNN model. Two magnitudes calculated from two magnetic vectors of the two sensor tags were added to feature vectors.

Sensor data arriving at the RFID reader were often unbalanced. Sometimes, data from only one tag arrived, possibly because the tag-to-reader distances differed or the radio waves encountered interference. In the future, we will test other RFID settings and use tags with multiple sensors.

6 Conclusions and Future Work

We used passive, high-functional RFID tags with magnetic sensor to detect touch positions, as a form of battery-free gesture input for wearable devices. The prototype includes a goggle-type device, a ring with a magnet, and software for detecting touch positions via machine-learning. We defined six touch points on the face and evaluated the accuracy of touch and no touch classification. The classification accuracy during learning phase was 83%, but dropped to 65% during the classification phase. Thus, the performance must be improved; in the future, we will enhance the accuracy of real-time classification, and define more touch points and gesture inputs.

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