FingMag: Finger Identification Method for Smartwatch

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Keunwoo Park
Korea Advanced Institute of Science and Technology

Geehyuk Lee
Korea Advanced Institute of Science and Technology

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Keunwoo Park
HCI Lab, School of Computing, KAIST
Daejeon, South Korea
keunwoo@kaist.ac.kr

Geehyuk Lee
HCI Lab, School of Computing, KAIST
Daejeon, South Korea
geehyuk@gmail.com

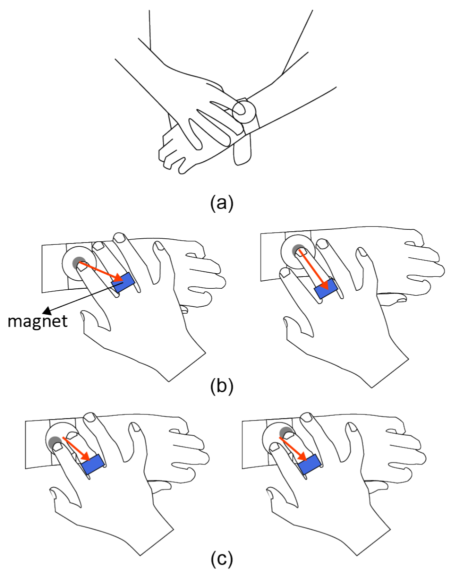

Figure 1: (a) Typical usage posture for a smartwatch. User holds up both arms in front of his/her body. (b) Relative magnet position is dependent on the finger touching the screen, and (c) on touch point.

KEYWORDS
Smartwatch; Finger Identification

ABSTRACT

Interacting with a smartwatch is difficult owing to its small touchscreen. A general strategy to overcome the limitations of the small screen is to increase the input vocabulary. A popular approach to do this is to distinguish fingers and assign different functions to them. As a finger identification method for a smartwatch, we propose FingMag, a machine-learning-based method that identifies the finger on the screen with the help of a ring. For this identification, the finger's touch position and the magnetic field from a magnet embedded in the ring are used. In an offline evaluation using data collected from 12 participants, we show that FingMag can identify the finger with an accuracy of 96.21% in stationary geomagnetic conditions.

INTRODUCTION

A smartwatch has limitations regarding interaction because of its small touchscreen size. For example, launching an application is difficult because the screen can show only a few icons at a time. A general strategy to overcome the limitation of the small screen is to increase the input vocabulary. A popular approach [2, 5, 7] is to distinguish fingers and assign different functions to different fingers. For example, a different function executes when different fingers tap the same button.

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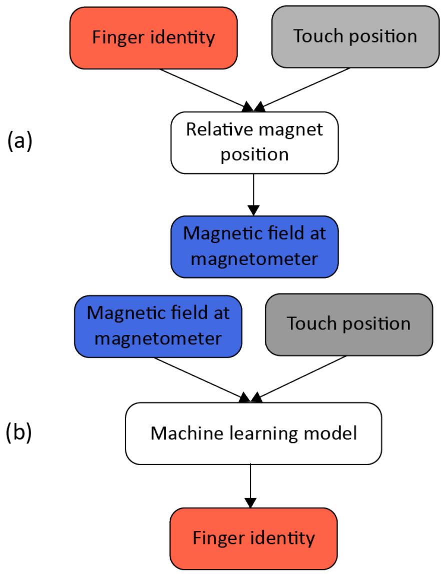

Figure 2: FingMag method: (a) Physical inference underlying FingMag method, and (b) inverse problem for FingMag method

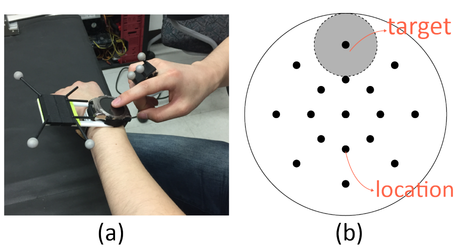

Figure 3: Data collection for determining magnet orientation: (a) smartwatch and ring with optical markers, and (b) targets on smartwatch.

As a finger identification method for a smartwatch, we propose a method called FingMag. As illustrated in Figure 1, a user wears a smartwatch on the left hand and a magnet ring on the middle finger of the right hand. The magnetic field vector measured at the internal magnetometer of the smartwatch is then determined by the position and orientation of the magnet relative to the magnetometer. We assumed a typical usage posture for a smartwatch as shown in Figure 1a. This is a posture in which a user holds up the arms in front of his/her body. In the posture, the orientation of the magnet remains nearly unchanged and the relative position of the magnet indicates which finger is touching the screen and its touch position on the screen (Figure 1b—c). Based on this reasoning (Figure 2a), we speculated that the identity of the finger touching the screen might be inferred inversely from the magnetic field vector measured by the internal magnetometer and the position of the touching finger on the screen. In this scenario, the problem to be solved is an inverse problem and may be ill-posed. We chose to explore the feasibility of this problem experimentally in this study. As the inverse problem is mathematically complicated, we chose to use a machine-learning approach where the input is the touch position and the magnetic field vector and output comprise the finger identity, as illustrated in Figure 2b.

RELATED WORK

Many studies have proposed methods for distinguishing between the fingers of a touch point. They utilized hand images [11], depth images [4], and color markers attached to fingers [6]. For these methods, a camera needs to be at a certain distance from hand in order to capture an appropriate image of the hand. Therefore, these methods cannot be applied to a smartwatch owing to its form factor. Other sensors have been used, such as electromyography sensors [2] and an optical sensors [7]. Although the sensors do not require a certain distance, wearing sensor devices in everyday life may be burdensome to users. Meanwhile, Tritap [5] identified fingers only with a smartwatch. It used a raw capacitive touch image to distinguish between the thumb, index, and middle finger. However, Tritap required the user to touch a touchscreen in an exaggerated posture, in order to achieve a high accuracy.

Magnets have been used to interact with wearable devices in many studies. Abracadabra [8] used a magnet for a user to move a cursor. With Nenya [1], a user could use a ring having a magnet attached to it as an input device. uTrack [3] tracked a magnet's 3D position in space using a similar method. TRing [10] used a magnet tracking technology to interact with physical objects.

FINGMAG PROTOTYPE

The prototype consists of a smartwatch (LG Urbane) and a permanent magnet. The smartwatch includes a magnetometer (AK8963). We use Scikit-Learn [9] as a machine learning model. There were many design parameters that we needed to determine before the main experiment, including the

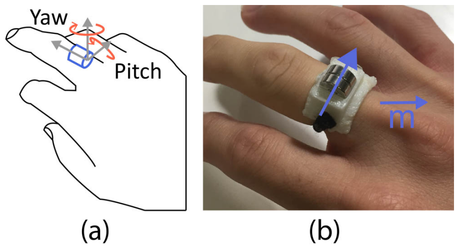

Figure 4: Orientation of magnet: (a) pitch and yaw angles of virtual magnet in simulation, and (b) final determined orientation of magnet.

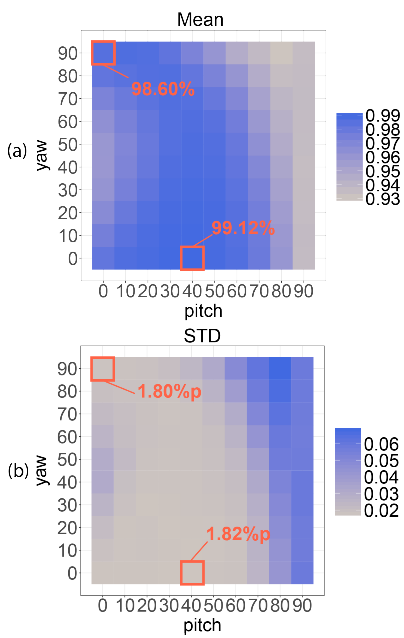

Figure 5: Predicted accuracies for different magnet orientations: (a) means and (b) standard deviations of cross-validation scores.

finger that wears the ring, the size and strength of the magnet, and the orientation of the magnet. We decided to put the magnet on the user's middle finger, since it is the closest point to the smartwatch when the user uses the index, middle, and ring finger. We selected a neodymium magnet that was small enough to be embedded in a ring but strong enough for the smartwatch to measure its magnetic field when it was put on a finger. The magnetic moment of the magnet was 170.90×10^{-3} A m^2. The length and diameter of the magnet were 6 mm and 7 mm, respectively. While most of the design parameters could be determined by trial and error, the orientation of the magnet was not easy to determine and required a systematic approach.

Determining Magnet Orientation

We collected orientation and position data of a ring and a smartwatch while users were using the smartwatch touchscreen, and conducted a computer simulation to determine the magnet orientation based on the collected data.

Data Collection Procedure. We recruited 12 participants (1 female, ages = 19 to 24). All were right handed. Participants wore a smartwatch on the left wrist and a 3D-printed ring with optical markers (without a magnet) on it on their right middle finger (Figure 3a). The participants were instructed to tap on targets shown on the smartwatch. There were five blocks in the data collection procedure. In each block, targets appeared at 17 positions as illustrated in Figure 3b. The finger required to be used was written in the target (e.g., "I" for an index finger). A target appeared twice for the same finger per position. In total, 102 ($17 \times 3 \times 2$) targets appeared randomly in each block. The diameter of the touchscreen was 35 mm (320 by 320 pixels), and the diameter of the target was 100 pixels. We asked the participants to maintain a comfortable and consistent posture throughout the blocks. When a participant tapped on a target, the touch point, the position, and orientation of both, the smartwatch and the ring, were recorded. Touch points were recorded by the smartwatch while other data were collected by an Optitrack system with five cameras.

Simulation and Analysis. The simulation involved putting a virtual magnet on the finger. First, we put a virtual magnet on the finger in a particular orientation. Then, based on the recorded position and the orientation data of the smartwatch and the finger, we calculated the magnetic field at the smartwatch position. In this way, we obtained magnetic field data for every tap. Next, we calculated the finger classification accuracy for each participant using the five-fold cross-validation method. We used touch points (x, y) and simulated magnetic fields (mx, my, mz) for the machine learning features. We used a support vector machine (SVM) with a linear kernel for the classifier ($C = 1.0$). We excluded data from one participant owing to a tracker problem. Therefore, we used data from only 11 participants.

To find an appropriate magnet orientation, we observed how the magnet's orientation affected the finger classification accuracy. We changed the pitch and yaw from 0° to 90° at 10° intervals. Figure 4a shows how we defined the pitch and yaw of a magnet relative to a finger. We tried 100 different magnet orientations. The average finger classification accuracies of each magnet orientation are shown in Figure 5. There were two orientations that showed approximately equal high accuracy. Between the two, we chose an orientation with a 90° yaw angle for simplicity of design. The final design of the ring based on this result is shown in Figure 4b.

OFFLINE EVALUATION: HANDLING POSTURE VARIATIONS AND VALIDATING FEASIBILITY

The goal of the evaluation was two-fold. The first goal was to examine the effect of arm posture changes on the accuracy of the FingMag method. The reasoning leading to the FingMag method given in the Introduction has a weak link. The assumption of a "typical hand posture" may be an ideal assumption. We expected that the assumed hand posture, as shown in Figure 1, would be a stable one supported by the two arms and the eye gaze from the head to the smartwatch. However, the angle between the two hands may change between uses, and the angle deviation may be a source of error. One way to cope with this problem is to use training data collected in different postures. We examined this possibility in the experiment. The second goal of the evaluation was to estimate the finger identification accuracy that the FingMag method can achieve in a static geomagnetic field condition, assuming some hand posture variations from the typical hand posture.

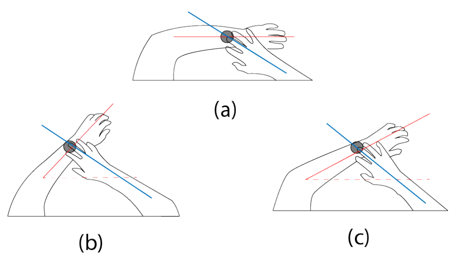

Figure 6: Three hand postures used in offline evaluation: (a) 0°, **(b)** 60°, **and (c)** 30°

Figure 7: Setup for data collection for offline evaluation: (a) side view and (b) top view.

Data Collection Procedure

We recruited 12 participants for this experiment (4 females, age = 19 to 30). All were right handed. We used the FingMag prototype described in the previous section. In order to collect data for different angles between two hands, we controlled the angle between the left arm and the body plane as shown in Figure 6. The resulting angles between the two hands varied approximately from 30° to 90°. This procedure had seven blocks and data were collected in three different postures. The task for each block was identical to the task in the previous magnet orientation determining procedure. The angles between the left arm and the body for the three postures were 0° (posture A), 60° (posture B), and 30° (posture C). Participants used posture A in block 1, 3, and 5, posture B in block 2, 4, and 6, and finally posture C in block 7. The smartwatch logged the touch point and magnetic sensor output for each tap.

We asked participants to use the smartwatch in a comfortable body posture while maintaining the required arm posture. To help participants pose and maintain the left arm at the required angle, we provided a visual guide, as shown in Figure 7. Participants stood in front of a table, and a piece of paper with parallel lines was placed in front of them. Participants lifted the left arm and aligned the

Table 1: **Test configurations in offline evaluation and their classification accuracy results.**

	Training (block)	Testing (block)	Accuracy (%)	SD of Acc (%p)
Test 1	1,3	5	91.99	6.01
Test 2	1,2,3,4	5,6	96.12	3.95
Test 3	1,2,3,4	7	96.41	3.97
Test 4	1,2,3,4	5,6,7	96.21	2.91

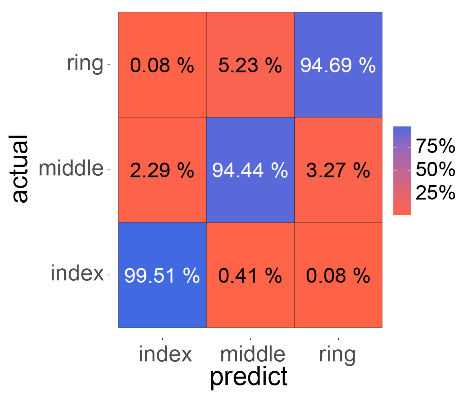

Figure 8: Confusion matrix among fingers from offline evaluation (Test 4).

arm to the parallel lines. They took off the ring and rested for a minute between blocks. A calibration procedure to compensate for the effect of the geomagnetic field was included in each block. The smartwatch measured the geomagnetic field for 1 s before starting the block, and subtracted the measured value from the subsequent magnetic field measurements.

Finger Classification Test

We conducted four classification tests. The training data and test data for all the tests are summarized in Table 1. *Test 1* is a baseline case where only data with posture A was used. *Test 2* was for the case where the postures of the training data and test data were the same. *Test 3* was for the case where the postures of the training data and test data were different. Finally, an overall classification accuracy was evaluated in *Test 4*. The data from blocks 1,2,3 and 4 were used for training, and the data from blocks 5, 6 and 7 were used for testing. We used a personalized classifier. The classifier was an SVM with a Radial Basis Function (RBF) kernel ($C = 2, \gamma = 2$).

The average accuracies of *Test 1, 2, 3,* and *4* are listed in Table 1. We found that it is possible to classify fingers in a single posture from *Test 1*. We think the low accuracy of *Test 1* is due to the small size of the training data. We found that it was possible to classify tapped fingers in varying postures if data from the varying postures were used as training data for *Test 2* (*96.12%*). For *Test 3*, we expect that it may be possible to classify tapped fingers even though a user used a posture that was not in training (*96.41%*). The overall accuracy of the FingMag prototype was *96.21%* (*Test 4*).

The confusion matrix of *Test 4* (Figure 8) indicates that the misclassification rate was highest between the middle finger and the ring finger. During the data collection procedure, we observed that some participants twisted their hand to tap with a ring finger. They tended to tap with a side of the ring finger. This behavioral pattern might have had an effect on the results of the evaluation.

CONCLUSION AND FUTURE WORK

In this paper, we presented FingMag, a novel finger identification method. We determined, via a simulation, the best orientation of the magnet in the ring for FingMag. We then conducted an offline evaluation of FingMag and were able to show that it could achieve a finger identification accuracy of 96.21% while allowing some variation of the hand posture in a static geomagnetic field condition.

The magnetometer not only measures the magnetic field from the finger-worn magnet but also measures the geomagnetic field. As the geomagnetic field measured by the magnetometer will depend on the orientation of the user, it will be a source of error if the user uses the touchscreen while rotating. The first problem to tackle in our future work is to develop a method to isolate and compensate for the effect of the geomagnetic field.

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