Touch Sensing on the Forearm Using the Electrical Impedance Method

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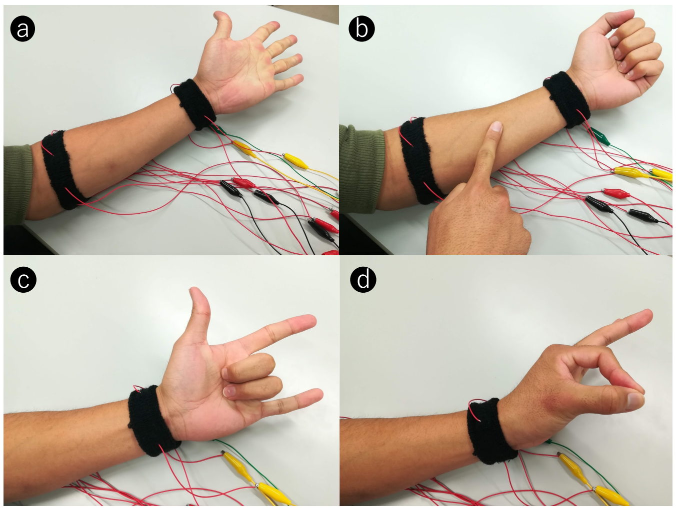

Fig. 1: (a) Bands with electrodes attached, to be worn by the user. (b) Touching the forearm. (c) Performing *Spider-man*. (d) Performing *Index pinch*.

***Abstract*—We present a novel on-skin touch sensing approach based on the electrical impedance method (EIM). Our approach enables the user to detect touch across the surface of the forearm by wearing two bands, one each on the lower and upper forearm. EIM uses a conductive substance to identify the area being touched. We focused on the electrical conductivity of the skin and applied EIM to the forearm. The two bands have electrodes on the inside. Signals are applied to these electrodes, and the resulting voltage on the surface of the skin is then measured. The advantages of our approach are that it works over a large area of the forearm, and can recognize both hand gestures and touch.**

***Index Terms*—Electrical Impedance Method, On-Skin Input, Wearable Devices**

I. Introduction

Most wearable devices, such as smart watches, have small interaction areas and thus they have occlusion and fat finger problems [1]. To alleviate these problems, researchers have previously explored the use of human skin as an interactive surface, thus increasing the opportunities for new interactions. Human skin is readily available and quickly accessible, and we can touch our body without looking. Furthermore, compared to wearable devices, skin is sufficiently large for meaningful interaction.

Several applications using human skin as an interactive surface have been proposed, such as cameras [2]–[4], infrared sensors [5]–[7], capacitive sensing [8]–[10], acoustic sensing [11]–[13], magnetic sensing [14], [15], and electrical field sensing [16], [17]. However, they often require users to wear an RGB/depth camera, result in occlusion problem, or a limited touch area.

In this paper, we propose a touch detection approach that works anywhere on the surface of the forearm. Our system also recognizes hand gestures. To achieve this, we exploited the electrical conductivity of the skin and applied the electrical impedance method (EIM) to the forearm. EIM was originally developed for medical purposes, such as monitoring ventilation and detecting breast cancers. Recently, it has been applied to the field of human-computer interaction (HCI) as an approach for identifying touch positions. In our approach, the user wears two bands. These serve as electrodes on the forearm. The system identifies touches and hand gestures by applying a machine learning algorithm to the voltages detected by the electrodes. Our approach enables touch position identification across a large area of the forearm and has hand gesture recognition capabilities (Fig. 1).

II. Related Work

In this section, we summarize two related research areas: touch input on the skin, and applications of the EIM.

A. On-Skin Input

There are many approaches to skin touch sensing. Ogata et al. [2], [3], and Harrison et al. [4] proposed camera-based approaches, in which touch is detected based on images captured by a camera attached to a smart watch or the shoulder. However, they have occlusion problem that user's hand may hide the touch positions.

Skin Buttons [5] and LumiWatch [6] made it possible to detect touch around the periphery of a smart watch by attaching infrared sensors to the side. The problem with these approach is that the touch-detectable area is narrow. WatchSense [7] makes it possible to detect touch on the forearm by wearing infrared sensors near the elbow. This approach addresses the problem of the narrow detection area, and the system can detect hover gestures as well as touch. However, occlusion can still be a problem because the actual position touched may be hidden by the user's hand.

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Weigel et al. [8] developed flexible and stretchable sensors for resistive touch sensing. DuoSkin [9], which was proposed by Kato et al., realizes mutual capacitive sensing on the skin by pasting gold foil onto it. Aditya et al. [10] created a thin and flexible multi-touch sensor that can be affixed to the skin, and a design tool. The sensors used in these approaches can be attached to any area of the human body, but the detectable area is still limited.

Harrison et al. [11] developed a system to detect touch on the forearm by attaching bio-acoustic sensors to the arm. Mujidiya et al. [12] presented a method for recognizing finger swipes and grasping gestures on the forearm by having the user wear an ultrasonic receiver on the arm and an ultrasonic transmitter on the opposite finger. Zhang et al. [13] suggested attaching an acoustic receiver to a smart watch to detect touch motion around its periphery, but the touch-detectable area is limited in this case. Chan et al. [14] and Huang et al. [15] developed a system to detect the finger gestures by attaching a magnet to the thumb, and attaching magnetic sensors to the other fingers. A compact sensor that can be attached to the fingertip is attractive, but, again, the detectable area is limited.

Zhang et al. [16] proposed attaching receiving electrodes to a smart watch and a ring-shaped transmitting electrode to the finger of the opposite hand, to enable touch sensing between the forearm and the back of the hand. This approach can also detect continuous finger tracking, but cannot detect touch when the electrodes are not worn. AuraSense [17], detects peripheral touches by attaching both the transmitting and receiving electrodes to the smart watch. With this approach, it is possible to achieve hand gesture and touch detection, as well as continuous finger tracking. However, the touch-detectable area is narrow, at about $30\,\mathrm{mm}$ from the smart watch.

B. Electrical Impedance Method

Electrical Impedance Method (EIM) is a non-invasive medical technology used for simple procedures such as chest examinations. In EIM, electrodes are installed around the target area or volume, and the voltage at each electrode is measured. The internal state of the area is evaluated by reconstructing images based on the measured voltages; this method is called electrical impedance tomography (EIT).

In the field of HCI, EIM is used for touch position identification and gesture recognition. Yoon et al. developed iSoft [18], which achieves touch sensing using soft conductive materials. MultiSoft [19] is an improved version of iSoft. Zhang et al. [20] fabricated a touch detection system by spraying conductive splays onto various objects and attaching electrodes around the sprayed area. They also proposed a system that recognizes scribbles on paper by coating the back of paper with a pattern of conductive material [21]. Zhang et al. [22], [23] recognized finger and hand gestures by installing electrodes on a wristband. Our approach is similar to these sensing techniques, but none of the previous method use EIM for touch detection on the skin.

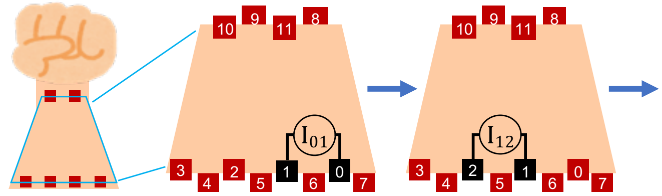


Fig. 2: Schematic diagram of the electro-impedance method, on which our approach is based. The generated signal is applied between a pair of adjacent electrodes, we measure the voltages at all of the other electrodes in turn.

III. Approach

We applied EIM to identify touch positions on the forearm. Fig. 2 shows an overview of our approach. Our detection field, the surface of the forearm, is more like a cylinder than a flat and uniform surface. In many cases, the upper forearm is thicker than the lower forearm. Therefore, we attached electrodes in a circle around the top and bottom of the forearm, that is, four electrodes are attached in a circle around the lower forearm and the other eight electrodes are attached in a circle around the upper forearm. Fig. 1(a) shows our working prototype of the band–type electrodes. We could also attach electrodes to the inside of the strap of the smart watch.

We adopted a machine learning technique to identify the touch positions on the forearm. The voltages detected by the electrodes are input into the machine learning algorithm. In our approach, first, a touch event is detected by a touch/no-touch classifier. When the classifier detects a touch, the touch position identifier identifies the touch position. One advantage of our approach is that it can also recognize hand gestures based on the same voltage data, collected by the same device. The gesture classifier can recognize hand gestures when the skin is not touched.

IV. Implementation

In this sectionwe explain the implementation of our voltage-sensing hardware, and touch input and gesture recognition software, which is based on a machine learning algorithm.

A. Electric circuit

A schematic diagram of the electric circuit is shown in the Fig. 3. We attached 12 electrodes to the forearm.

The waveform generator is controlled by a micro-controller to generate a sine wave of $200\,\mathrm{kHz}$, $2\,\mathrm{V_{p-p}}$. A frequency of $200\,\mathrm{kHz}$ is well suited to our purpose because, due to the electrical characteristics of the surface of the human body, this relatively low frequency is desirable for inducing changes in the impedance at the positions touched [24]. The generated sine wave is amplified to $4\,\mathrm{V_{p-p}}$ by the operational amplifier.

We applied the generated signal to every pair of adjacent electrodes (Fig. 2). One multiplexer is used to select the electrode to receive the generated signal, and the other is used to select the adjacent electrode for grounding. After a pair of electrodes has been selected and the generated signal is

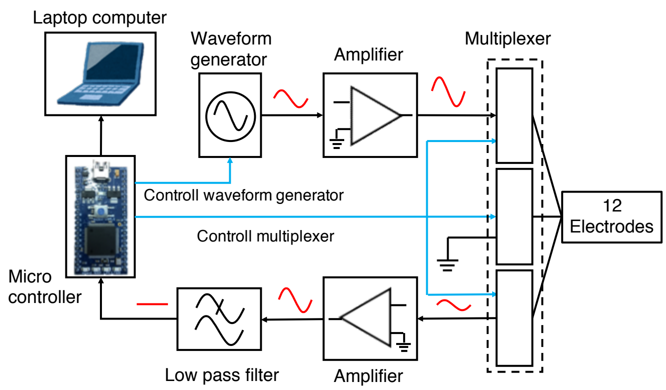


Fig. 3: Schematic diagram of the electric circuit.

applied between them, we measure the voltages at all of the other electrodes in turn. The measuring electrode is selected by another multiplexer. Before switching a measuring electrode, we wait $5\,\mathrm{ms}$ for the voltage to stabilize.

We measure the voltages in the following manner: first, the voltage at the measuring electrode is amplified by the operational amplifier. Then, it is rectified by a low-pass filter, and read by a micro-controller. The voltage reads are transmitted from the micro-controller to a laptop computer, and used as the input data for the touch position and hand gesture recognition software.

We use the mbed LPC1768[1] micro-controller, which is connected to the laptop computer with a USB cable. We use the AD5930[2] integrated circuit as a waveform generator, and two AD817s[3] as operational amplifiers. We use three CD74HC4067[4] as multiplexers, and each channel is connected to each electrode. We use 12 WhiteSensor WS/RT[5] as the electrodes.

B. Touch Identification and Gesture Recognition

In our current implementation, the touch/gesture recognition process begins with touch detection, where the system detects whether there is a touch or not using a touch/no-touch classifier. The classifier is implemented as a support vector machine (SVM) using the scikit-learn library in Python. Then, when a touch is detected by the first classifier, the touch position identifier identifies its position based on the input data. The touch position identifier is also implemented by an SVM.

When the first classifier does not detect a touch, the gesture classifier, which is also implemented as an SVM, recognizes the user's hand gesture.

One frame consists of 12 electrodes (inserting) $\times$ 10 electrodes (measuring) $\times$ 25 (samples) = 3,000 voltage samples.

[1]https://os.mbed.com/platforms/mbed-LPC1768/

[2]https://www.analog.com/media/en/technical-documentation/data-sheets/AD5930.pdf

[3]https://www.analog.com/media/en/technical-documentation/data-sheets/AD817.pdf

[4]https://www.sparkfun.com/datasheets/IC/cd74hc4067.pdf

[5]https://www.mets-tokyo.jp/dcms_media/other/catalog-whitesensor.pdf

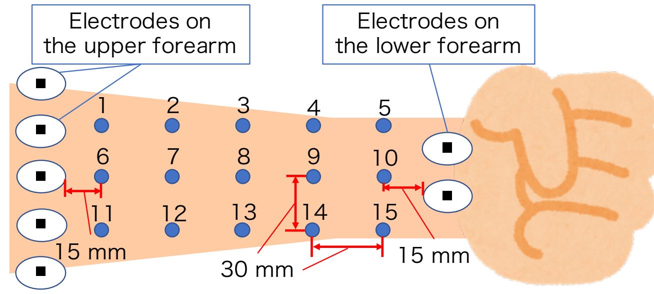


Fig. 4: The 15 touch points.

Decreasing the number of measurements at each electrode from 25 samples reduces the accuracy of identification. Conversely, increasing it increases the measurement time but does not improve the accuracy so much. Therefore, we use 25 samples. It takes about 0.91 seconds to collect and analyze one frame.

V. Evaluation

We carried out two pilot studies to evaluate the performance of our approach. In one study, we evaluated the accuracy of the touch position identification. We evaluated the accuracy of the hand gesture recognition algorithm in the other study.

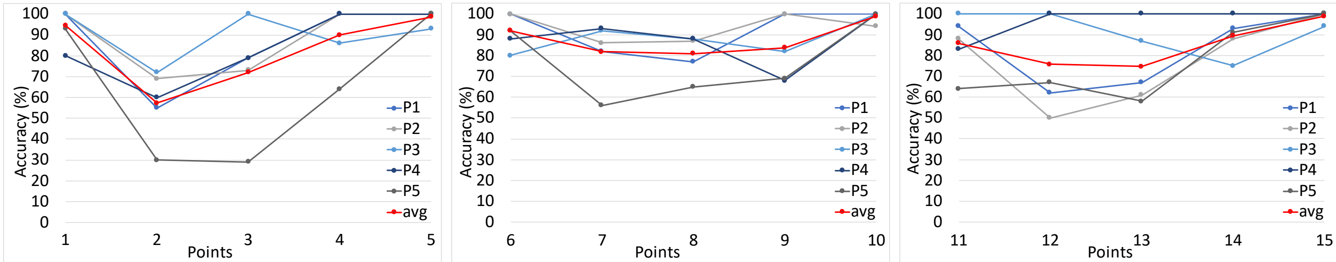
A. Pilot Study 1

We carried out a pilot study on the accuracy of the touch position identification. Five right-handed male volunteers (P1–P5; mean age, 23 years) participated in this pilot study.

1) Procedure: The experimenter measured the circumference of each participant's lower/upper forearms. Next, the experimenter attached 12 electrodes to each participant's non-dominant forearm, as shown in Fig. 4. The experimenter carefully attached the electrodes to ensure that they were equally spaced around the circumference of the lower and upper forearms. The experimenter then calibrated the amplification factor of the operational amplifier so that the measured voltage did not exceed the maximum voltage measurable by the micro-controller ($3.3\,\mathrm{V}$). Next, the experimenter used a highlighter pen to mark 3×5 points on the participant's non-dominant forearm as touch points. The distance between the adjacent points was $30\,\mathrm{mm}$, as was the case in the previous study [4]. The distance between the circumference of the lower and upper forearm was $150\,\mathrm{mm}$ Hence, the closest touch point was $15\,\mathrm{mm}$ from the electrodes.

The participants sat on a chair and placed their non-dominant elbow on a desk. They were asked to choose the wrist and elbow angles that they would find easy to maintain over the course of the experiment. They were also asked to adjust the height of the chair so that they could easily maintain their posture.

The experimenter prepared a peace of paper similar to that shown in Fig. 4, on which there was a figure of the forearm and the number (1-15) of each touch point. The experimenter showed this pease of paper to the participants, and asked



(a) #1–5 (b) #6–10 (c) #11–15

Fig. 5: Results of pilot study 1 for each point.

TABLE I: RESULTS FROM PILOT STUDY 1 FOR EACH PARTICIPANT

Participant	P1	P2	P3	P4	P5
Circumference of the upper forearm (mm)	280	250	230	260	225
Circumference of the lower forearm (mm)	170	160	150	165	155
Distance between electrodes on the upper forearm (mm)	35.0	31.3	28.8	32.5	28.1
Distance between electrodes on the lower forearm (mm)	42.5	40.0	37.5	41.3	38.8
Accuracy (%)	87.0	86.0	90.0	89.0	72.0

them to touch the position on the skin corresponding to the number indicated by the experimenter. Before each touch test, the experimenter asked the participants to maintain the *no-touch* state for about 10 seconds, and then to touch each point sequentially, as instructed. The experimenter asked the participants to keep touching each point for 10 seconds. We measured 10 frames in each touch test, with intervals of approximately 2 seconds between each touch point.

We treated the task of maintaining the no-touch state and then touching all 15 points as one session. The participants completed five consecutive sessions. Thus, we collected 5 (participants) × 5 (sessions) × 15 (points) × 10 (frames) = 3,750 (frames) of touch data, and 5 (participants) × 5 (sessions) × 10 (frames) = 250 (frames) of no-touch data.

2) Learning: We divided all of the data into training and test data at a ratio of 7:3. We determined the parameters of the SVM (kernel, γ, C) for both classifiers for each participant, using a grid-search with five cross-validations for the training data. The accuracy of the SVM was evaluated using the test data. To classify the touch/no-touch frames, we used data from 50 no-touch frames and data from 50 frames at touch point #8. We used 750 frames of touch data to identify the touch positions.

3) Result: The average detection accuracy of the touch/no-touch classifier for five participants was 100%; in other words, we detected all of the touches. The average accuracy of the touch position identification for the five participants was 84.8% (SD = 10.8%). The size of the lower/upper forearm and identification accuracy for each participant are summarized in Table I. Although the accuracy of P5 was remarkably poor, this was possibly due to the experimenter setting the measured voltage incorrectly during calibration.[6]

[6]We verified the measured voltage of P5 after five sessions, and found it to be lower than assumed.

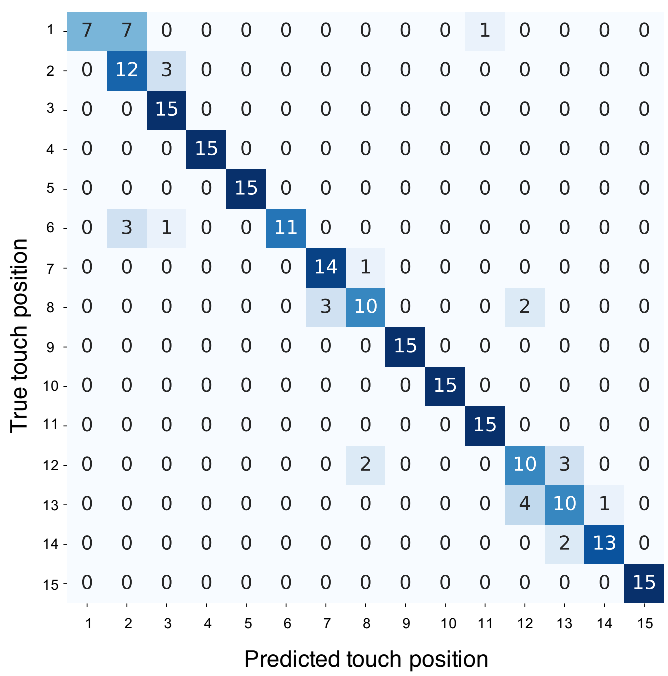


Fig. 6: The confusion matrix of P1.

Fig. 5 shows the accuracy for each participant at each point. As shown by the red line indicating the average accuracy for each of the participants, points closer to the lower forearm were detected more accurately. The accuracy was worse in the middle positions, but better again on the upper forearm.

The confusion matrix for P1 is shown in Fig. 6. Neighboring points were misclassified most frequently, such as on the upper left (e.g., #1, #2), center (e.g., #7, #8), and lower right (e.g., #12, #13). Other participants also exhibited this

Fig. 7: Gesture sets.

tendency, which suggest that the resolution, which depends on the number of electrodes, might affect identification accuracy.

The internal structure is another possible cause of the decrease in accuracy at the upper forearm. There are no large muscles on the lower forearm, but there are many large muscles on the upper forearm, such as the brachioradialis, palmaris longus, and flexor carpi ulnaris muscles. Generally, muscles have low electrical resistance, so some people have low impedance on the upper forearm. On the other hand, the impedance changes on the upper forearms of people who have a lot of internal fat in their forearms are sufficient. In the future, we will investigate these possibilities and determine the optimum positions and number of electrodes.

B. *Pilot Study 2*

Due to the similarity of our system to the previous hand gesture recognition systems [22], [23], our proposed method can be used to identify both hand gestures and touch positions. In this section, we briefly describe the pilot study that we carried out to evaluate the gesture recognition accuracy. We used the participants from pilot study 1 in this study.

1) Procedure: We prepared two sets of gestures: a set of hand gestures and a set of pinch gestures. We used the same hand gesture set as in the previous studies [22], [23], which includes *Relax, Fist, Stretch, Right, Left, Thumb Up, Spider-Man,* and *Index Pinch* (Fig. 7). The pinch gesture set is a set of a *micro* gestures,with more subtle differences than in the other hand gesture sets. The pinch gesture set includes *Relax, Index Pinch, Middle Pinch, Ring Pinch,* and *Little Pinch* (Fig. 7). *Relax* gesture in both sets correspond to the hand and the fingers being in a neutral position.

The experimenter instructed the participants as follows. First, the experimenter asked the participants to adjust the height of their chair and maintain the angle of their elbow over the course of the experiment. Then, the experimenter asked the participants to perform specific gestures from the hand gesture set, one by one. The experimenter performed each gesture for the participants, told them its name, and showed them a picture of the gesture on the display. The participants held each gesture for approximately 5 seconds. We measured five frames during each gesture. The interval between gestures was approximately 3 seconds. We treated the sequential performance of all gestures as one session. The participants completed five consecutive sessions. The same experiment was repeated for the pinch gestures.

Hence, we collected 5 (participants) × 5 (sessions) × 8 (gestures) × 5 (frames) = 1,000 (frames) for the hand gesture set. Also, we collected 5 (participants) × 5 (sessions) × 5 (gestures) × 5 (frames) = 625 (frames) for the pinch gesture set.

TABLE II: THE RECOGNITION ACCURACY FOR EACH PARTICIPANT IN PILOT STUDY 2

Participant	P1	P2	P3	P4	P5	avg
Hand gesture set (%)	97.0	96.0	99.0	98.0	100	98.0
Pinch gesture set (%)	100	100	97.0	100	98.0	99.0

2) Result: The recognition accuracies of the hand and pinch gesture sets were 98.0 and 99.0%, respectively. The recognition accuracies for each participant are shown in the Table II. We obtained better results than in previous studies [22], [23]; the improvement in accuracy is due to the number of measurement samples per frame, which is larger than in the previous studies.

VI. Application

It is possible to input characters into small wearable device such as smart watches. The user typically interacts with a 10-key input system and there are 12 buttons on the forearm. A typical 10-key input system for a smart watch includes functions such as enter, delete or keypad switching (e.g., letters to numbers). These functions can be controlled by the hand gestures. For example, after the user inputs characters by touching the forearm, s/he can input 'enter' by making *ThumbUp*. If the user makes a mistake, the user can erase it by making *IndexPinch*. To change the position of the pointer, the user can perform *Left* and *Right*. It is also possible to switch from the keypad for character input to the leypad for numeric input by performing *Stretch*. This application solves the occlusion and fat finger problems, because it enables 10-key input without needing the user being required to touch the screen.

VII. Conclusion

In this paper, for the first time we used the EIM for touch position identification on human skin. This enabled us to identify the touch positions across a large area of the forearm; 11 hand gestures could also be recognized.

In the future, we would like to achieve real-time tracking of the finger on the skin. The current system needs too long time to acquire one frame of the voltage pattern. One reason for this is the waiting time prior to changing the signaling electrode. We stabilized the measured voltages by implementing a $5\,\mathrm{ms}$ waiting time prior to switching between electrodes. Therefore, a total of $600\,\mathrm{ms}$ is taken up by waiting during the aquisition of a single frame. We will reduce this waiting time by exploring the reason for the instability.

For more practical use, we need to evaluate the robustness and accuracy of the system in more situations, such as when the rings are not well aligned, when the arm is rotated, or when the skin gets wet. We also intend to evaluate the long-term performance of the device.

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