Exploring Subtle Foot Plantar-based Gestures with Sock-placed Pressure Sensors

Koumei Fukahori
The University of Tokyo
Tokyo, Japan
furaga@is.s.u-tokyo.ac.jp

Daisuke Sakamoto
The University of Tokyo
Tokyo, Japan
d.sakamoto@acm.org

Takeo Igarashi
The University of Tokyo
Tokyo, Japan
takeo@acm.org

ABSTRACT
We propose subtle foot-based gestures named *foot plantar-based (FPB) gestures* that are used with sock-placed pressure sensors. In this system, the user can control a computing device by changing his or her foot plantar distributions, e.g., pressing the floor with his/her toe. Because such foot movement is subtle, it is suitable for use especially in a public space such as a crowded train. In this study, we first conduct a guessability study to design a user-defined gesture set for interaction with a computing device. Then, we implement a gesture recognizer with a machine learning technique. To avoid unexpected gesture activations, we also collect foot plantar pressure patterns made during daily activities such as walking, as negative training data. Additionally, we evaluate the unobservability of FPB gestures by using crowdsourcing. Finally, we conclude with several applications to further illustrate the utility of FPB gestures.

Author Keywords
User-defined gesture; foot plantar sensing device; sock-placed interface; hands-free interaction.

ACM Classification Keywords
H.5.2. Information interfaces and presentation, e.g., HCI: User Interfaces - Input devices and strategies

INTRODUCTION
We use our hands to control computing devices (e.g. personal computers and mobile devices). However, in life, our hands often get busy, so we are not always able to use them. Some examples are: 1) when the user's hands are busy such as during cooking or carrying bags with both hands, 2) when upper-body space is limited for use such as in a crowded train, or 3) when the user's fingers are stiff with cold.

To address this, a number of interaction techniques using foot-based gestures have been proposed such as kicking gestures [1], toe/heel rotations [24], and tapping the floor [3]. However, due to the fact that these foot-based gestures require users to move their feet largely, they are not private and sometimes serve as an annoyance to people around the user. Therefore, it is difficult to use these gestures in a public space, e.g. in a train or on the street. In this work, we propose subtle foot-based gestures named *foot plantar-based (FPB) gestures* used with sock-placed pressure sensors (Figure 1). The user can control a computing device by changing the pressure distributions under his/her feet, e.g., by pressing the floor with his/her toe. FPB gestures are subtle; they are suitable for use especially in a public space and are able to be used both in and out of shoes.

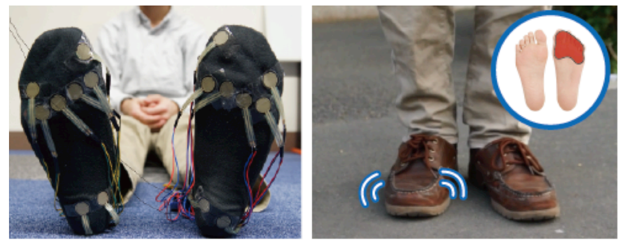


Figure 1. Left: user wearing sock-placed pressure sensors named *Sockswitch*. Right: performing gesture of pressing floor with toes in shoes.

There are three goals in this study: designing a suitable FPB gesture set for interaction with a computing device, implementing a gesture recognizer for FPB gestures (we use a machine learning technique for the gesture recognition), and evaluating how unobservable FPB gestures are. To achieve these goals, we conducted four studies. In the first study, we asked 20 participants to design an appropriate FPB gesture set for 29 operations. On the basis of the collected gesture ideas, we designed a user-defined gesture set [29] that consists of 15 FPB gestures. The second and third studies were for collecting training data for our gesture recognizer. In the second study, we collected foot plantar pressure patterns appearing when performing FPB gestures. We measured the pressure patterns of participants with simple sock-placed pressure sensors called *Sockswitch* (Figure 1, Left). In the third study, we collected foot plantar pressure patterns appearing during daily activities such as walking. We use the pressure patterns to avoid unexpected gesture activations made during daily activities. As a result, the accuracy of the gesture classification was 91.3%, and the accuracy of the binary classification of a FPB gesture and daily motion was

CHI 2015, April 18-23, 2015, Seoul, Republic of Korea.

http://dx.doi.org/10.1145/2702123.2702308

99.4%. In the last study, we asked crowd workers to watch videos where an actor is performing foot-based gestures and to guess which gesture was performed. The result of this study confirmed that FPB gestures are significantly more difficult to observe than other foot-based gestures.

Finally, we conclude with showing several applications to further illustrate the utility of our system. In summary, the main contributions of this research are:

- Designing a user-defined FPB gesture set.
- Implementing a FPB gesture recognizer that can prevent unexpected gesture activations during daily activities.
- Evaluating how unobservable FPB gestures are.

RELATED WORK

Foot Plantar Pressure Measurement System

A number of devices for sensing pressure distributions between the feet and the floor have been proposed. These devices can be categorized into two classes: sensing floors and footwear (shoe-placed or sock-placed) sensors. A sensing floor is a floor that contains pressure sensors underneath. For example, Paradiso et al. proposed Magic Carpet [15], which detects the pressure and position of the feet by using a grid of piezoelectric wires and a pair of Doppler radars. Richardson et al. proposed Z-tiles [20], interlocked tiles that contain a number of force-sensitive resistor sensors. Augsten et al. [3] used frustrated total internal reflection (FTIR) and front diffused illumination (front DI) to allow a camera beneath a floor to capture foot pressure images. These sensing floors can precisely detect a user's foot plantar pressure distribution and the position where the user stands. However, because these techniques are limited to a fixed position, it is difficult to use them outdoors such as in a train.

A number of footwear (shoe-placed or sock-placed) pressure sensors have been proposed ([25, 28] and a survey paper is [19]). These footwear devices have several pressure sensors on their foot plantar. However, these sensors have mainly been used in specific application domains such as physiotherapy [9, 12] and sport science [11, 22] for passive monitoring. In contrast, we use sock-placed pressure sensors to actively control computing devices.

Foot-based Gesture Interaction

Many researchers have been exploring interaction techniques with the foot. Pearson et al. [17] proposed a foot operated cursor-positioning device called the “planar slide mole” and assessed its performance against a mouse for target selection. Takeuchi [26] proposed foot tap gestures to operate a map navigating system. Several researches have proposed foot-based interaction techniques to move around virtual reality (VR) environment [6, 10, 13]. Scott et al. [24] evaluated the use of four foot gestures: lifting a toe/heel and foot rotations pivoting the heel/toe. Alexander et al. [1] conducted user studies and propose suitable foot gesture patterns for controlling mobile devices. As an example of systems using footwear pressure sensors, Paradiso et al. [16] proposed a dance system where a user can control background music by using foot-based gestures. As another example, Papetti [14] proposed a sandal-placed foot tapping interface with audio-tactile feedback. Although these foot-based gestures allow the user to control devices comfortably, these gestures are too large; they are not private and sometimes serve as an annoyance (eyesore) to people around the user. In contrast, the FPB gestures we propose are subtle; they are private and not annoying to others.

A supplemental feature of Multitoe [3] is most similar to our system. The system uses a sensing floor, and the user can control a PC game by changing his or her foot plantar pressure distributions. We extend this idea to design a user-defined gesture set for various interactions with computing devices, and to implement a gesture recognizer that works even in real-world applications.

Subtle and Private Input Device

Several subtle interaction techniques have previously been proposed. Costanza et al. [7] used electromyography (EMG) to detect subtle motionless gestures for mobile computing. Saponas et al. [23] extended this idea and proposed a gesture set for use in real-world applications. Wolf et al. [30] explored how microinteractions such as hand gestures allow executing a secondary task without interrupting the primary tasks such as controlling mobile applications while driving. Amento et al. [2] proposed a wrist-mounted bio-acoustic device for sensing fingertip gestures. The freedom of fingertip gestures has been expanded to allow users to point to a 3D position (uTrack [5]) and to use a fingertip as a touchpad (FingerPad [4]). These subtle interaction techniques usually use the hands for interaction. Therefore, these techniques are limited for use in situations where the user’s hands are busy. On the other hand, brain-computing devices have been proposed [18, 27]. Using these devices, a user can control a computer only by thinking of a command in his or her mind. However, it is currently difficult to recognize a command precisely. In contrast, our FPB gestures can be used even when the user’s hands are busy and can be recognized relatively precisely.

User-defined Gesture Set

User-defined gestures are designed by asking users to design a gesture that they believe is suitable for each computing operation. This approach works effectively when an input device is not common and it is not clear how users want to handle it. This approach has been used to design gestures for tabletop [29] and mobile devices [21] and to design (large) foot-based gestures such as moving a foot leftward and tracing a circle with it [1]. We also adapt this approach to design a suitable FPB gesture set.

DESIGNING A USER DEFINED GESTURE SET

We first design a FPB gesture set for 29 operations in 6 categories (Table 1). The 29 operations are based on

Alexander et al.'s work [1]. They investigated an appropriate "large" foot-based gesture set, e.g., kicking and tracing a circle with a foot, for controlling mobile devices. We refer mainly to their operation list because our motivation is similar to their research.

Study 1: Collecting Gesture Ideas for the 29 Operations

To design a gesture set, we first conduct a guessability study. We ask 20 participants to think and generate an appropriate gesture idea for each of the 29 operations.

Procedure

We show participants the 29 operations one by one and ask them to consider a FPB gesture that they believe is most appropriate for each operation. The categories of gestures are always presented in the same order; the gestures in those categories are presented randomly. During this study, participants wear a head mounted display (HMD) and a pair of earphones (Figure 2, Right). We use HMD and earphones for the study because they are private output methods, which are suitable for a subtle and private input technique. The HMD shows a video and the earphones plays a sound that explains each operation. For example, when we show a participant the operation "*answer phone call,*" the HMD shows the call screen of an iPhone 5 (Figure 2, Left), and the earphones play a ringtone.

To minimize the bias on generating FPB gesture ideas, we showed as general as possible interfaces to participants (e.g., rectangles in a grid pattern for *"item selection"* category). However, only *"answer/ignore phone call"* may be strongly biased because the two operations shows horizontally aligned buttons (Figure 2, Left). Therefore, we also tested vibration interface without screen (Left-bottom in Table 1).

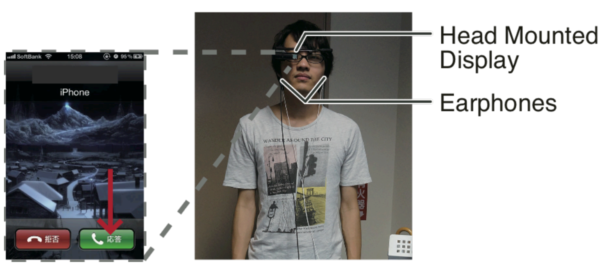


Figure 2. A participant wears HMD and earphones. The HMD is showing a video for *"answer phone call"*.

The participants propose a FPB gesture by performing the gesture while orally explaining it. Also, we give five instructions: 1) participants need to execute each operation without shifting or lifting their foot plantar, 2) they can use both feet if necessary, 3) they need not worry about conflicts of gestures among the operations, 4) they need not worry about technical issues in gesture recognition, and 5) they can say "no idea" if they cannot come up with any FPB gesture. We manually sketch the proposed gestures like illustrations in Table 1.

Participants

Twenty volunteers between 23 - 59 years old (average was 26.8 years old) participated in the study. All of them were Japanese. Only one participant was left-footed. Only two participants regularly use a foot-based input device (a dance game in a game center). No participants had any injury that would inhibit foot movement.

Result

We obtained 17 - 20 gesture ideas for each operation and observed 563 gesture ideas in total. The participants said "no idea" 17 times. The supplemental material A shows the gesture ideas we obtained for each operation.

Gesture Selection Process and Algorithm

Next, we choose a user-defined gesture set based on the 563 gesture ideas collected in Study 1. To remove the subjective selection process, we design an algorithm for selecting gestures automatically. We can see the gesture selection process as an energy minimizing problem. Intuitively, we follow three rules (Figure 3): 1) choose a gesture that many participants proposed for each operation, 2) choose symmetric gestures for a symmetric operation pair, and 3) avoid choosing the same gesture (or similar gestures) for multiple operations. However, we do not care about conflicts among operations that are seldom executed in the same situation, e.g., *"Next track"* in media control and *"Next page"* in browser navigation.

Formally, we minimize the following energy function for

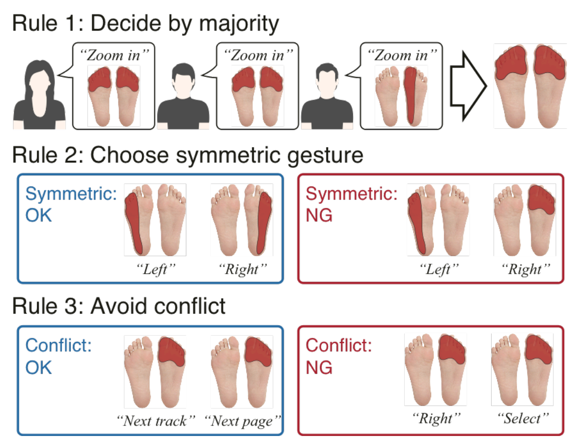


Figure 3. Three rules for designing our user-defined gesture set

mapping L from a set of operations O to a set of FPB gestures G.

$$\min_{L:O\to G} E_{Agree} = \min_{L:O\to G} -\sum_{i\in O} |P_{iL(i)}|$$

$$\text{s.t} \quad \{\mathrm{i},\mathrm{j}\} \in S_O \Rightarrow \{L(i), L(j)\} \in S_G,$$

$$\exists \mathrm{C_O} \in \{C_O\},\ \ i,j \in C_O \Rightarrow L(i) \neq L(j), \{L(i), L(j)\} \notin I_G$$

1. Item selection	Left
1. Item selection	Right
1. Item selection	Up
1. Item selection	Down
1. Item selection	Select
2. Map navigation	Move viewpoint leftward
2. Map navigation	Move viewpoint rightward
2. Map navigation	Move viewpoint upward
2. Map navigation	Move viewpoint downward
2. Map navigation	Rotate map clockwise
2. Map navigation	Rotate map counter-clockwise
2. Map navigation	Zoom in
2. Map navigation	Zoom out
3. Media control	Play/pause
3. Media control	Previous track
3. Media control	Next track
3. Media control	Volume up
3. Media control	Volume down
4. Phone control	Answer phone call
4. Phone control	Ignore phone call
4. Phone call	Answer phone call (call with vibration)
4. Phone call	Ignore phone call (call with vibration)
5. Browser navigation	End phone call
5. Browser navigation	Home screen
5. Browser navigation	Previous page
5. Browser navigation	Next page
5. Browser navigation	Focus address bar
6. Gesture recognition	Activate (x 2)
6. Gesture recognition	Deactivate (x 2)

Table 1. Our user-defined gesture set designed through Study 1

$|P_{ig}|$ is the number of participants that proposed a gesture g for an operation i, S_O is a set of symmetric operation pairs, S_G is a set of symmetric gesture pairs, and C_O is a set of operations that should not be in conflict with each other. I_G is a set of similar gesture pairs, e.g., the upper-left and upper-right gestures in Table 2. We enumerate the elements of each set in the supplemental material B.

Implementation

We implement a solver of the energy minimizing problem in C#. The basic strategy is: 1) enumerate possible gesture pairs for each symmetric operation pair (or gestures for an operation without any symmetric counterpart) and 2) accept the gesture pairs one by one in the order of the total number of participants that proposed the two gestures. If a gesture pair conflicts with already accepted operation-gesture mappings, it is rejected.

Result

The gesture set consisted of 15 different FPB gestures (Table 2). Each illustration means a FPB gesture of pressing the floor with the part (parts) highlighted in red. For example, the upper-left in Table 2 means the FPB gesture of pressing the floor with the left toe (i.e., each illustration shows foot plantar in a mirror.). There was one gesture assigned into multiple operations, i.e., $|C_O| < 29$. However, in practice, any conflict will not happen because the operations are seldom used in the same situation. Thus, we suppose that our system understands which operation should be executed depending on the situation.

In this study, participants preferred FPB gestures made using the right foot because most of them were right-footed. In fact, the left-footed participant tended to propose gestures by using the left foot. In practice, it is better to allow users to freely switch which foot to use for performing each FPB gesture.

FOOT PLANTAR-BASED GESTURE RECOGNITION

We implement a gesture recognizer for the 15 FPB gestures designed in Study 1. We use a machine learning technique (support vector machine, or SVM) for the gesture recognition. To collect training data (foot plantar pressure patterns), we conduct two data collection studies. In the first study (Study 2), we measure foot plantar pressure patterns while participants perform FPB gestures. We use the pressure patterns in Study 2 as positive training data. In the second study (Study 3), we measure plantar pressure patterns while participants perform daily activities, such as walking or standing up. We use the pressure patterns in Study 3 as negative training data to avoid unexpected gesture activations during daily activities. Our gesture recognizer is implemented in C# and running on a 2.5GHz CPU (Quad Core) and 8GB RAM computer.

Sockswitch: Sock-placed Pressure Sensors

For sensing foot plantar pressure distributions, we develop a simple foot plantar pressure measurement system named *Sockswitch* (Figure 4, Left). Sockswitch is a pair of socks, each of which has a microcontroller (ATmega328P on Arduino Fio) connected to eight force-sensing resistor (Interlink Electronics, FSR 402) pressure sensors. As a pre-resistor of each FSR, we set 330 Ω resistor in a circuit. We follow Wertsch et al.'s work [28] to decide the arrangement of the sensors (Figure 4, Right). We place sensors 1 - 7 according to their work and append sensor 8 to sense the movements around the user's little toes. Pressure data is sampled every 50 milliseconds. The data is transmitted to the host computer by wireless (ZigBee serial) connection.

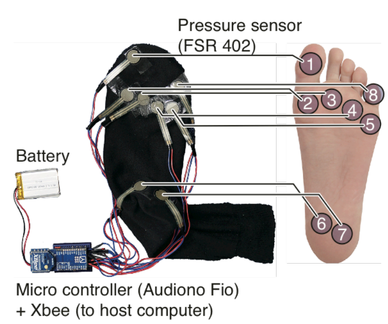


Figure 4. Left: Sockswitch system configuration. Right: locations of pressure sensors for one foot.

Gesture Recognition Algorithm

Our gesture recognizer analyzes the pressure data received from Sockswitch and recognizes FPB gestures. In our approach, our recognizer directly recognizes 14 FPB gestures except *"double pressing with right toe"* (lower-right of Table 2). The system notices that the double pressing gesture is performed when the single pressing gesture (middle-left of Table 2) is performed twice in 0.5 seconds. This is a process similar to a click and double clicks on computing devices.

We show the process of our gesture recognition in Figure 5. First, when our system receives time series data of pressure distribution from Sockswitch, it calculates I(t) as the intensity of movement of each foot. Our system segments a time span, where I(t) is more than a threshold (0.1) (plus a 200ms buffer on either end).

$$\mathrm{I}(t) = (f_i(t) - E_i(t) - f_j(t) + E_j(t))\ \max(0, \frac{df_i}{dt}(t))$$

$$\text{s.t.} \quad \{\mathrm{i}, \mathrm{j}\} = \max_{i,j \in sensors} f_i(t) - E_i(t) - f_j(t) + E_j(t)$$

$f_i(t)$ is the pressure value of sensor i at the time t. $f_i(t)$ has been normalized from raw data from FSR 402; range of [0, 1023] as integer into [0, 1] as float. $E_\mathrm{i}(t)$ is an exponential moving average (EMA, $\alpha = 0.3$) of $f_i(t)$. $E_\mathrm{i}(t)$ is used as a baseline of $f_i(t)$. The baseline $E_\mathrm{i}(t)$ adaptively changes according to the user's body weight and barycentric position of the user. Therefore we do not conduct any pre-calibration for our gesture recognition.

Next, our system classifies each segment (a movement of the foot plantar) into "a daily motion" or "a FPB gesture" with SVM. We use 146 features for the classification. The features include the maximum and minimum value of each pressure sensor (32 features), the inner product of $I(t)$ and the time derivative for each pressure ($\int I(t) \frac{df_i}{dt}(t)dt$, 16 features), and the minimum of the summation of the pressure values on each foot plantar (2 features). We also calculate a 64-point discrete Fourier transform (DFT) of the waveform of each pressure sensor and use the amplitude and the phase of the three lowest frequency components ($16 \times 3 \times 2 = 96$ features). We use an open source library, LIBSVM[1], for the implementation of SVM. We use the pressure data obtained in Study 2 as training data of a FPB gesture and one obtained in Study 3 as a daily motion.

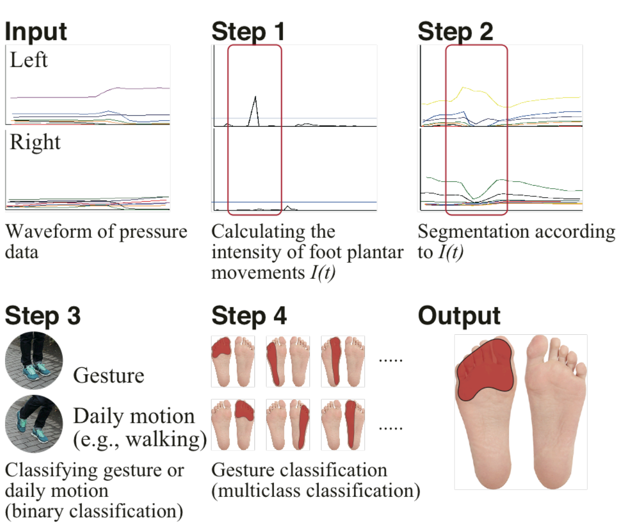


Figure 5. Workflow of our gesture recognition

Finally, if the segment is classified as a FPB gesture, the system classifies it into one of the 14 FPB gestures with another SVM. We use the same 146 features described in the previous paragraph. We use the pressure data obtained in Study 2 as training data for each gesture.

Study 2: Collecting Pressure Patterns during FPB Gestures

Procedure

We asked each participant to wear Sockswitch and to perform the 14 FPB gestures (*"double pressing with right toe"* excluded from the 15). We show each gesture one by one in random order, and the participants perform the gesture. Each gesture is shown 10 times during the study; each participant performs FPB gestures 140 times in total. Our system measures foot plantar pressure patterns while each participant is performing the gestures. During the study, we also videotape them for later verification.

Participants

Five volunteers between 22 - 24 years old (average was 23.4 years old) participated in the study. Only one participant was left-footed. No participant regularly uses a foot-based input device. No participant had any injury inhibiting foot movement. Their foot sizes were between 25.5 and 27.5 cm (average was 26.4 cm). Their body weights were between 51 and 85 kg (average was 62 kg)

Result

We obtained $10 \times 5 = 50$ pressure patterns for each gesture and 700 patterns in total. To evaluate the classification accuracy, we used the two cross validation protocols proposed in [24]: within-participant stratified cross

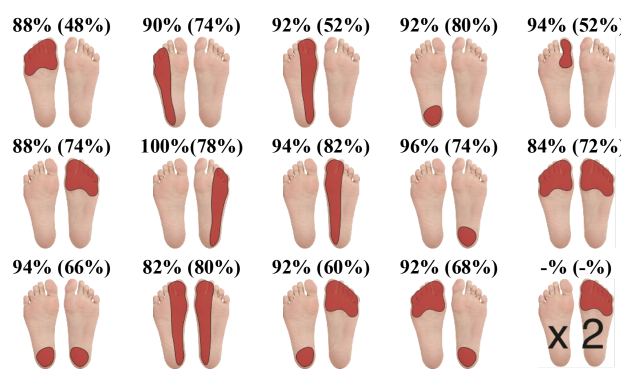


Table 2. Gesture classification accuracy on WP (outside parentheses) and LOPO (in parentheses).

[1] http://www.csie.ntu.edu.tw/~cjlin/libsvm/

validation (WP) and leave-one-participant-out cross validation (LOPO). WP assumes user-dependency and LOPO assumes user-independency respectively. Table 2 shows the classification accuracies on the two protocols.

Overall, the average accuracy of the 14 FPB gestures was 91.3% on WP and 56.2% on LOPO. This means that our gesture classifier is strongly user-dependent. In other words, FPB gestures can be classified accurately if using the training data from the same user.

Study 3: Collecting Pressure Patterns during Daily Activities

Procedure

We asked each participant to wear Sockswitch and go to a university co-op to buy something to drink as a reward. We follow them with holding a PC to record the sensor data from Sockswitch. First, each participant sits down on a chair in our lab. After we start the measurement, he stands up, go to the store, buys a drink, goes back to our lab, and sits down on the chair again. Then, we finish the measurement. Through this study, we could collect pressure patterns made while sitting, standing up, walking, stopping, and so on. During the study, we also videotape participants for later verification.

Participants

Five volunteers, who had participated in Study 2, participated in this study. Each study was performed soon after Study 2.

Result

We obtained 1824 seconds of pressure data in total. We segmented all of the pressure data by executing the segmentation process (the upper row of Figure 5), yielding 299 pressure patterns. Table 3 shows the accuracies of binary classification of FPB gesture and daily motion on WP and LOPO.

Overall, the accuracy on WP was 99.4% and that on LOPO was 58.0%. This means the binary classification is also strongly user-dependent. On the other hand, the precision of FPB gesture and the recall of daily motion were surprisingly good on both of the two protocols. This is because sensor values for walking were completely different from those for standing. For example, 1) each data segment was long, 2) the max value of $I(t)$ in the segment was large, and 3) all sensor values change synchronously.

	Precision	Recall	F-measure
FPB gesture	0.99 (0.97)	1 (0.41)	0.99 (0.58)
Daily motion	1 (0.41)	0.98 (0.97)	0.99 (0.58)

Table 3. Accuracy of binary classification of FPB gesture and daily motion on WP (outside parentheses) and LOPO (in parentheses).

EVALUATING UNOBSERVABILITY OF FOOT PLANTAR-BASED GESTURES

The key idea of FPB gestures is making foot-based gestures difficult to observe. FPB gestures should not be observed by people around the user. In this section, we conduct a user experiment to measure how unobservable FPB gestures are by testing the following three hypotheses:

H.1. It is more difficult to identify which FPB gesture was performed than other foot-based gestures.

H.2. It is more difficult to notice the user's foot movement while he or she is performing a FPB gesture than other foot-based gestures.

H.3. It is as difficult to notice the user's foot movement while he or she is performing a FPB gesture as while the user is doing nothing.

In this study, we compare the unobservability of FPB gestures with one of Alexander et al.'s gestures [1] and Scott et al.'s gestures [24].

Study 4: Evaluating Unobservability of FPB Gestures by Using Crowdsourcing

We conduct a user experiment on a crowdsourcing service named *CrowdFlower*[2]. We evaluate the unobservability of 35 gestures in 4 categories: 15 FPB gestures, Alexander et al.'s 13 gestures [1], Scott et al.'s 6 gestures [24] and performing no gesture (Table 4).

Category 1. FPB gestures (15 gestures)
See Table 2
Category 2. Alexander et al.'s gestures (13 gestures)
Single tap
Double tap
Double tap forward/leftward/rightward (3)
Trace a clockwise/counter-clockwise circle (2)
Trace a clockwise/counter-clockwise arc (2)
Kick forward/backward/leftward/rightward (4)
Category 3. Scott et al.'s gestures (6 gestures)
Up toe
Up heel
Rotate foot leftward/rightward pivoting toe (2)
Rotate foot leftward/rightward pivoting heel (2)
Category 4. No gesture (1 gestures)
Do nothing

Table 4. 35 gestures in 4 category evaluated in Study 4

Procedure

Crowd workers are asked to watch a video of a trained user performing a foot-based gesture and to try and guess which gesture was performed (Figure 6). We show each video by using <video> tag of HTML 5. The workers can watch a video repeatedly. For this study, we prepare 35 videos; each video shows an actor performing one of the 35 gestures. The length of each video was less than 10 seconds. The workers answer which gesture was performed in a five-choice question. The five choices consist of the correct

[2] http://crowdflower.com

answer, three dummy answers, and "no gesture was performed”. The dummy answers are randomly selected from the same category of the correct answer. For example, if the correct answer is any of the FPB gestures, the dummy answers are also any of the FPB gestures. Also, the workers answered how confidently they answered the question on a 5-level Likert scale (“Definitely,” “Very probably,” “Probably,” “Possibly,” and “Not sure”).

Figure 6. Question for our crowdsourcing evaluation

Quality control

To ensure the quality of the user study results, one task page contains one test question. If a worker selects a wrong answer on the test question, we assume that he or she is unreliable, and his/her answers are rejected. For this study, we prepare 189 test questions. First, we prepare 190 questions; Alexander et al.’s 13 gestures and Scott et al.’s 6 gestures respectively appear in 10 questions. Then, we asked two lab members to answer the 190 questions. We used the 189 questions that both of the lab members answered correctly as our test questions.

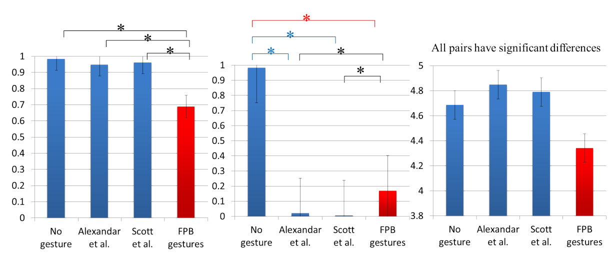
Questions and crowd workers

We prepared 3700 questions (+189 test questions). The 34 foot-based gesture videos respectively appear in 100 questions, and the no-gesture video appears in 300 questions. The 300 questions for the no-gesture video consist of 3 sets × 100 questions. Each question has four dummy answers and the dummy answers in each set are selected from the same category (FPB gestures, Alexander et al.’s gestures or Scott et al.’s gestures). A task consists of five questions including one test question. A crowd worker can take 25 tasks (100 answers and 25 answers for test questions) at maximum. The workers can stop their tasks in the middle. Overall, 909 workers participated in this study, and the average number of answers was 4.1. We paid the workers 5 cents for a task, and the total cost of this crowdsourcing was $162.

Result

We evaluated the unobservability of gestures with three metrics: accuracy, number of questions wrongly answered as “no gesture was performed,” and confidence for each answer on a 5-level Likert scale. Accuracy means how difficult it was to identify each gesture, the number for “No gesture” means how difficult it was to notice the actor’s foot movement while he was performing each gesture, and confidence means the subjective difficulty of each question.

Figure 7 shows the averages of each category for the three metrics. For example, the averaged accuracy of FPB gestures was 68.9%, and the other categories’ accuracies were above 94%. To compare the averages among categories, we performed a non-parametric multiple comparison test (Steel-Dwass test [8]). As a result, there were statistical significances ($p < 0.05$) between FPB gestures and the other foot-based gestures in all metrics (black annotations in Figure 7). This means that FPB gestures were significantly more difficult to identify and notice (H.1 and H.2). On the other hand, for number of “No gesture,” the average of FPB gestures was significantly smaller than that for no gesture (red annotations in Figure 7). This means that a lot of workers could notice the actor’s foot movement when performing FPB gestures (against H.3).



(a) Accuracy (b) # of “No gesture” (c) Confidence

Figure 7. Result of Study 4 for each category

To compare each gesture, we also performed a Steel-Dwass test among the 37 question sets (34 × 100 questions for the foot-based gestures and 3 × 100 questions for no gesture). We show the p-value of each pair in the supplemental material C. Then, for each FPB gesture, we counted the number of other foot-based gestures, Alexander et al.’s and Scott et al.’s, that were significantly different from the FPB gestures in accuracy ($p < 0.05$, the last row of Table 5). Nine FPB gestures were significantly different (more difficult to observe) from most of the 19 other foot-based gestures in accuracy (≥ 18). On the other hand, three FPB gestures had almost no differences with other gestures (≤

Accuracy	74%	55%	59%	59%	57%	74%	60%	59%	67%	84%	78%	83%	66%	60%	88%
# of "No gesture"	17%	23%	24%	15%	20%	16%	16%	21%	22%	11%	13%	13%	17%	20%	7%
Confidence	4.5	4.1	4.4	4.1	4.2	4.4	4.3	4.3	4.4	4.6	4.5	4.6	4.0	4.2	4.7
Differences with large gestures	12/19	19/19	19/19	19/19	18/19	12/19	19/19	19/19	18/19	1/19	7/19	1/19	19/19	19/19	0/19

Table 5. Result of Study 4 for each FPB gesture

1). This is likely because the three gestures are difficult to perform subtly, and the actor unconsciously moved his feet largely. The small number of differences for *"pressing the floor with both heels"* (= 7) is due to the same reason. The two gestures of pressing with the left or right toe also had relatively few differences (= 12). We consider this is because we recorded each video from the front of the actor; the movements of the toes were more visible than those of the other parts of the foot plantar.

APPLICATION

The design of the FPB gestures is aimed at hands-free interaction with subtle foot movements. They are suitable for controlling mobile devices in a public space such as answering/ignoring a phone call on a crowded train. Likewise, they are suitable for use in situations where we cannot or should not use our hands, e.g., scrolling the web page of a recipe while cooking or browsing a slide during a presentation with hand gestures like in a TED presentation. Here, we briefly present some possible applications with FPB gestures.

Secure Interface

Because FPB gestures are subtle, they may be used for security systems such as ATMs. As a proof of concept, we implemented a GUI application for inputting a secret number (Figure 8-a, left). In this application, users wear a head mounted display (HMD), and the HMD shows a number pad. Users control a cursor on the number pad by using the five FPB gestures in the item selection category (Table 1). We designed this interface by asking the 20 participants of Study 1 to design an interface for inputting numbers (we asked after Study 1) and choosing one that the most participants proposed.

As a simpler application, we also implement a password input system for unlocking a smartphone (Figure 8-a, right). The user can unlock a smartphone by performing several FPB gestures in pre-defined order.

Supporting PC control

FPB gestures can be used to support our PC work. For example, a participant in Study 1 commented *"I want to use FPB gestures to switch desktop windows while working on PC"*. We agree with his idea because it is tiring to move the user's hand from keyboard to mouse and then click an icon on task bar. Also, pressing Alt + Tab repeatedly until the target window appears is time-consuming. As a solution of this problem, we implemented a Windows service application where the user can switch desktop windows by performing FPB gestures (Figure 8-b). For example, in the accompanied video, a user is writing a thesis with TeX. He switches to bash by pressing a floor with the right-heel, to a pdf viewer with the right-toe and to a text editor with the left-heel.

Gaming interface

Our participants often said that they wanted to play a game with FPB gestures. To achieve this, we implemented a simple rhythm game (Figure 8-b). The main objective of this game is to press the floor with the foot plantar, following notes of music scrolling from the front. Each note is represented as an illustration of the left foot plantar or one of the right foot plantar. Users are required to press the floor with the left or right foot plantar.

Interface for Wearable Devices

It is possible to use FPB gestures to control a head-mounted display (HMD) such as Google Glass. Currently, voice recognition and hand-based gestures are proposed as the main input methods. However, these methods can be heard or seen by people around the user, which is not private and sometimes serves as an annoyance. In contrast, because FPB gestures are difficult to observe, they are suitable for use as an input method for HMDs, particularly in a public space.

A. Secure Interface:
Input secret number (left) and Unlock smartphone (right)

B. Supporting PC control

C. Gaming interface

Figure 8. Applications for FPB gestures

DISCUSSION

In this research, we conducted three studies to design and implement a FPB gesture system with sock-placed pressure sensors. From the result, our system successfully recognized FPB gestures with avoiding unexpected gesture activations during daily activities. The accuracy of the gesture classification was 91.3%, and the accuracy of the binary classification between a gesture and a daily motion was 99.4%. Though the number of participants of Study 2 and 3 is small, we consider that our concept, FPB gesture recognition with sock-placed sensors, was proven.

Then, we conducted a user study to evaluate how unobservable FPB gestures are (Study 4). The result confirmed that FPB gestures are significantly more difficult to observe than other foot-based gestures. On the other hand, the accuracy of FPB gestures was 68.9%. This percentage seems too large. However, in this study, we supposed one of the most severe situations; each video showed only the actor's lower-body and workers could watch the same video as many times as they wanted. In daily life, when we look at a person, we usually look at his/her upper body and can look at his/her movement only once. Considering this, we believe that the accuracy of 68.9% is small enough to confirm that FPB gestures are absolutely difficult to observe.

The result of Study 4 also shows that it is easy to notice that the user somewhat moves his foot while performing a FPB gesture. This seems to be against our motivation that a user can perform FPB gestures without being noticed. However, in daily life, our foot plantar frequently moves subtly during standing and sitting (see people around you). Thus, even if others notice the user's foot movement, they could not know whether the movement is a FPB gesture or a daily motion.

We used sock-placed pressure sensors for sensing foot plantar pressure distributions. However, it was possible to use shoe-placed pressure like *FootLogger*[3]. We used sock-placed sensors because they can cover wider situations rather than shoe-placed sensors. For example, in most Asian countries, people take off their shoes indoors but do not take off their socks. Further, a participant of Study 3 pointed out that sock-placed sensors are better because they can be stretched and worn by users even if their foot sizes are different. In fact, the five participants of Studies 2 and 3 (their foot sizes were 25.5 - 27.5 cm) could wear the same sock-placed sensors.

FPB gestures can be performed with subtle foot movements. However, in some cases, large foot gestures such as kicking forward and tracing a circle with the foot, might be more intuitive and easier to perform than FPB gestures. In practice, it would be better to allow users to use both FPB gestures and large foot gestures and to choose which gesture to use depending on the situation.

[3] http://vandrico.com/device/3l-labs-footlogger

Limitation and Future Work

In Studies 1, 2, and 3, all of the participants performed tasks while wearing low-heel shoes such as sneakers. However, if they were wearing high heels, gesture ideas and foot plantar pressure patterns would differ from the ones we obtained. Further, all of the participants in Study 1 were Japanese, which might bias FPB gesture ideas. It is future work to explore how shoes and cultural differences affect the design of the FPB gesture set and FPB gesture recognition.

In Study 3, we mainly collected pressure patterns during walking. Therefore, it might not be enough to prevent unexpected gesture activations during various activities, such as exercising or driving a car. Our gesture recognizer would be more robust if we collect pressure patterns during such activities as negative training data.

To perform a FPB gesture, a user needs to add force to the pressure sensors on his or her foot plantar. Therefore, it is difficult to perform a FPB gesture such as when sitting with folded legs. However, this problem would be addressed by attaching strain gage sensors along the foot fingers and detecting how each finger is hooked. It is future work to implement a FPB gesture recognizer with those additional sensors.

In this paper, we focused on subtle foot-based gestures used when a user is stopping (standing or sitting). However, we can consider ones used during walking or running, e.g., swinging the feet with adding force around the thumbs or the little toes. It is future work to explore subtle foot-based gestures when a user is moving.

Seven participants of Study 1 pointed out that FPB gestures are not suitable for executing complex operations such as map navigation. They said that it is difficult to perform FPB gestures quickly, and it is tiring to perform them many times. We consider that it is most suitable to use FPB gestures to execute a simple operation such as answering a phone call or playing/pausing a music player.

CONCLUSION

We proposed foot plantar-based (FPB) gestures, an interaction technique that uses sock-placed pressure sensors. We designed a user-defined gesture set and implemented a SVM gesture recognizer for FPB gestures. Our gesture recognizer can avoid unexpected gesture activation during daily activities such as walking. The accuracy of the gesture classification was 91.3%, and that of the binary classification of a FPB gesture and a daily motion was 99.4%. We also evaluated how unobservable each FPB gesture is and confirmed that FPB gestures are significantly more difficult to observe than existing foot-based gestures. Finally, we showed several applications of FPB gestures to illustrate their utility.

ACKNOWLEDGMENTS

This work was supported by JSPS KAKENHI Grant Number 26240027.

REFERENCES

1. Alexander, J., Han, T., Judd, W., Irani, P., and Subramanian, S., Putting Your Best Foot Forward: investigating real-world mappings for foot-based gestures. In *Proc. CHI'12*, 1229-1238.
2. Amento, B., Hill, W., and Terveen, L. The Sound of One Hand : a wrist-mounted bio-acoustic fingertip gesture interface. In *Proc CHI EA'02*, 724–725.
3. Augsten, T., Kaefer, K., Meusel, R., Fetzer, C., Kanitz, D., Stoff, T., Becker, T., Holz, C., and Baudisch, P. Multitoe: high-precision interaction with back-projected floors based on high-resolution multi-touch input. In *Proc. UIST '10*, 209-218.
4. Chan, L., Liang, R.H, Tsai, M.C., Chang, K.Y., Su, C.H., Chen, M.Y., Cheng, W.H., Chen, B.Y. FingerPad: private and subtle interaction using fingertips. In *Proc. UIST'13*, 255-260.
5. Chen, K.Y., Lyons, K., White, S., Patel, S. uTrack: 3D input using two magnetic sensors. In *Proc. UIST'13*, 237-244.
6. Choi, I., and Ricci, C. Foot-mounted gesture detection and its application in virtual environments. In *Proc. IEEE Internationa Conference on System, Man and Cybernetics '97*, 4248-4253.
7. Costanza, E., Inverso, S.A., Allen, R., and Maes, P. Intimate Interfaces in Action: assessing the usability and subtlety of EMG-based motionless gestures. In *Proc. CHI '07*, 819-828.
8. Dwass, M. Some k-sample rank-order tests. In *Essays in Honor of Harold Hotelling*. 198–202.
9. Edgar, S., Swyka, T., Fulk, G., and Sazonov, E.S. Wearable shoe-based device for rehabilitation of stroke patients. In *Proc. IEEE Engineering in Medicine and Biology Society'10*. 3772-3775.
10. Haan, G.D., Griffith, E.J., and Post, F.H. Using the WiiBalance Board TM as a low-cost VR interaction device. In *Proc. VRST '08*, 289-290.
11. Holleczek, T., Ruegg, A., Harms, H., and Troster, G. Textile pressure sensors for sports applications, In *Journal of Sensors '10*, 732-737.
12. Luo, Z.P., Berglund, L.J., and An, K.N. Validation of F-Scan pressure sensor system: a technical note. In *Journal of rehabilitation research and development 98*, 186–191.
13. Matthies, D.J.C., Muller, F., Anthes, C., and Kranzlmuller, D. ShoeSoleSense: proof of concept for a wearable foot interface for virtual and real environments. In *Proc. VRST'13*, 93-96.
14. Papetti, S., Fontana, F., Civolani, M., Berrezag, A., and Hayward V. Audio-tactile display of ground properties using interactive shoe. In *Proc. HAID'10*, 117-128.
15. Paradiso, J., Abler, C., Hsiao, K.Y., and Reynolds M. The Magic Carpet: physical sensing for immersive environmentse. In *Proc. CHI EA '97*, 1997.
16. Paradiso, J., Hu, E., and Hsiao, K.Y. Instrumented footwear for interactive dance. In *Proc. the XII Colloquium on Musical Informatics '98*, 89-92.
17. Pearson, G., and Weiser, M. Exploratory evaluation of a planar foot-operated cursor-positioning device. In Proc. *CHI '88*, 13-18.
18. Pike, M.F., Major, H.A., Porcheron, M., Sharples, S.C., and Wilson, M. L. Measuring the effect of think aloud protocols on workload using fNIRS. In *Proc. CHI '14*, pp. 3807–3816, 2013.
19. Razak, A.H.A., Zayegh, A., Begg, R.K., and Wahab, Y. Foot plantar pressure measurement system: a review. In *Journal of Sensors 2012*, 9884–912.
20. Richardson, B., Leydon, K., Fernstrom, M., and Paradiso, J.A. Z-Tiles: building blocks for modular , pressure-sensing floorspaces, In *Proc. CHI '04 EA*, 1529-1532.
21. Ruiz J., Li, Y., and Lank E., User-defined motion gestures for mobile interaction. In *Proc. CHI'11*, 197-206.
22. Salpavaara, T., Verho, J., Lekkala, J., and Halttunen, J. Wireless insole sensor system for plantar force measurements during sport events. In *Proc. IMEKO XIX World Congress on Fundamental and Applied Metrology'09*, 2118-2123
23. Saponas, T.S., Tan, D.S., Morris, D., Balakrishnan, R., Turner, J., and Landay, J.A. Enabling always-available input with muscle-computer interfaces. In *Proc. UIST '09*, 167-176.
24. Scott, J., Dearman, D., Yatani, K., and Truong, K.N. Sensing foot gestures from the pocket. In *Proc. UIST '10*, 199-208.
25. Sensoria. http://www.sensoriafitness.com/
26. Takeuchi, Y. Gilded Gait: reshaping the urban experience with augmented footsteps. In *Proc. UIST '10*, 185-188.
27. Tan, D. S., and Nijholt, A. *Brain-Computer Interfaces: applying our minds to human-computer interaction*. Springer, 2010.
28. Wertsch, J.J., Webster, J.G., and Tompkins, W.J. A portable insole plantar pressure measurement system. In *Journal of Rehabilitation Research and Development '92*, 13-18.
29. Wobbrock , J. O., Morris, M. R., and Wilson , A. D. User-defined gestures for surface computing. In *Proc. CHI '09*, 1083–1092, 2009.
30. Wolf, K., Rohs, M., Naumann, A., Müller, J., Laboratories, D.T., and Berlin, T.U. A taxonomy of microinteractions: defining microgestures based on ergonomic and scenario-dependent requirements. In *Proc. INTERACT '11*, 559-575.