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Ohnishi, Ayumi
Terada, Tsutomu
Tsukamoto, Masahiko

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A Method for Recognizing Postures and Gestures Using Foot Pressure Sensors

AYUMI OHNISHI^{1,a)} TSUTOMU TERADA^{1,2,b)} MASAHIKO TSUKAMOTO^{1,c)}

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Abstract: In this paper, we propose a method for recognizing postures and gestures by using foot pressure sensors, and we investigate optimal positions for pressure sensors on soles from the viewpoint of motion recognition accuracy. In experiments, the recognition accuracies of 22 kinds of daily postures and gestures were evaluated from foot-pressure sensor values. Furthermore, the optimum measurement points for high recognition accuracy were examined by evaluating combinations of two foot pressure measurement areas on a round-robin basis. As a result, when selecting the optimum two points for each user, the recognition accuracy was about 94.5% on average. The recognition accuracy of the averaged combinations of the best two combinations for all subjects was classified with an accuracy of about 91.9% on average. As a result of an evaluation to raise versatility, the average recognition accuracy in a three-point evaluation was 98.4%, which was almost the same with the recognition accuracy when using all 105 points. In anticipation of the applicability of this research result, two types of pressure sensing shoes were developed.

Keywords: foot pressure, posture recognition, gesture recognition, insole, shoes device

1. Introduction

Due to the miniaturization of sensors, it has become possible to acquire various contexts by wearing sensors. Commercial life log systems also have begun to appear, and context-aware services with wearable sensors are being introduced to support our daily lives. In the near future, more and more context-aware services will be generalized due to further improvements to the performance and miniaturization of sensors.

By attaching many sensors to the body, it is possible to acquire a lot of human motion data. However, since mounting multiple devices requires labor or cost, it is desirable that wearable devices are integrated into what people routinely use in life. Therefore, we focused on shoes because they are used on a daily basis, and they can be used to sense the feet, thus making it possible to collect a lot of information on the human body.

If actions were estimated from sensors built into shoes, it would be possible to sense human behaviors naturally when they are moving. This would be applicable in a lot of situations, not only in daily situations but also in sports or entertainment. Also, such shoe-type systems would become natural to use for users who are unfamiliar with charging or attaching/detaching devices, so they could be applied to systems used for the elderly and others.

In existing research, there are many examples of using shoes for sensing; however, the states of body parts other than the feet were not recognizable, such as postures. In addition, the optimal

sensor arrangement for estimating states was not studied in detail. By investigating which parts of the sole of the foot are effective for recognizing posture and motion, it would be possible to study how to efficiently place sensors to achieve a high recognition accuracy and a low power consumption; therefore, it is meaningful to examine the optimum measurement position.

In this research, we propose a method for recognizing body postures and motions from foot pressure information by using foot pressure distribution sensors mounted on shoes. Considering power consumption, it is desirable to estimate postures and motions with a small number of sensors. Therefore, the optimum number of sensors and sensor positions that can recognize everyday postures and motions with high accuracy were investigated.

The structure of this paper is described below. In Section 2, related research is introduced. In Section 3, we discuss two evaluation experiments and explain sensing shoes developed to measure foot pressure, and we describe future directions of this research in Section 4. Finally, we summarize the paper in Section 5.

2. Related Research

2.1 Foot Pressure Analysis

The measurement and analysis of pressure values applied to the soles of the feet have been studied. Zhou et al. tried to identify individuals from the way they walked by using a carpet-type pressure sensor sheet and identified them with an accuracy of 76.9% [1]. Sousa et al. tracked and identified people by using pressure sensor sheets and wearable accelerometers [2]. These studies focused on individual differences in walking or foot pressure changes, identified individuals from foot pressure analysis, and did not recognize posture or motion from foot pressure. However, since pressure sensor sheets stay in one location, it is difficult to record daily behaviors outside the home.

¹ Graduate School of Engineering, Kobe University, Kobe, Hyogo 657-8501, Japan

² PREST, JST, Kawaguchi, Saitama 332-0012, Japan

^{a)} ayumi@stu.kobe-u.ac.jp

^{b)} tsutomu@eedept.kobe-u.ac.jp

^{c)} tuka@kobe-u.ac.jp

In this research, shoes that are routinely worn on a daily basis, independent of location, and that recognize motions and postures by using low-cost pressure sensors were focused on.

2.2 Research on Recognizing Daily Behaviors

Starner et al. recognized users' daily behaviors by using a camera [3]. Many pieces of research have been conducted to recognize a user's actions by using cameras; however, the method of study depended on the place. It has become possible to recognize daily behaviors without depending on the place by using wearable sensors to recognize such behaviors.

As a daily context aware system that uses a wearable sensor, Tsubaki et al. recognized eleven kinds of motions or postures from body circumference changes by using a stretch sensor [4]. However, the sensor must be brought into close contact with multiple parts, such as the arms, legs, and belly of the body. Acceleration sensors have often been used for gesture recognition. Murao et al. evaluated 27 kinds of gestures by using 9 types of acceleration sensors and angular velocity sensors arranged on a board and evaluated the recognition accuracy when changing the position and number of sensors [5]. Watanabe et al. used small ultrasonic speakers on the arms and microphones on the chest to recognize gestures by using the change in ultrasonic volume and frequency change caused by the Doppler effect [6]. Microsoft's Kinect [7] could recognize a user's postures and gestures with infrared rays and depth sensors. Although the researchers in these studies acquired postures and motions that could be judged from their appearance, they had difficulty acquiring contexts that did not have large movements, for example, continually placing a load on one foot or making movements with the center of gravity of the body. If we could recognize everyday contexts with shoes, it would be convenient for users because shoes are relatively easy to maintain, and people usually wear shoes.

2.3 Research on Measuring Foot Pressure with a Wearable System

There is a huge body of existing work on different approaches and the application of shoe pressure sensors [8]. When analyzing walking by using a pressure sensor sheet, it is unnecessary to consider the arrangement of sensors. However, to measure the pressure of the soles by using a wearable device, we need to select positions for sensors where we can acquire the desired data with a high accuracy in consideration of power consumption and practicality. We will explain the research on using wearable systems such as shoes or socks with a focus on the sensor layout. Fukabori et al. developed a sock-type device called "Sockswitch" and built an interface by using user-defined minute ankle gestures [9]. With this device, 8 points on one foot (a total of 16 pressure sensors) were arranged at the center of the toes of the foot in order to perform a gesture. Hayama et al. measured the feet pressure by using an insole-type pressure sensor with 11 pressure sensors on one foot and compared pressure sensor values with measured values acquired on a force plate to estimate the trajectory of the foot pressure [10]. In this study, the sensor placement was decided on the basis of the characteristics of the foot sole load for each subject. Zhou et al. estimated the direction of a ball from a pressure

sensor sheet attached at three places that were hit when the ball was kicked by a football shoe [11]. Talavera et al. developed a wireless insole with a 14-point pressure sensor in a project called "WIISEL" in Europe [12]. In this project, walking data of people were obtained in large-scale demonstration experiments, and a fall risk analysis was performed mainly for elderly people. Since this insole had non-contact charging and used BLE communication, there were no connectors or cables; moreover, it was designed to have a low power consumption. However, sensor placement was not described in detail. These 14 sensor positions were decided uniquely by the authors, and no clear reasons why these 14 points were set were indicated. González et al. measured foot pressure and performed gait analysis [13], but his research focused only on walking behaviors in daily movement. Moufawad et al. classified sitting, standing and walking, using IMU sensors and foot pressure measurement insole, but other actions in daily life were not discussed [14]. Sazonov et al. estimated 14 types of daily postures or movements, such as standing, walking, running, cycling, etc., from the foot pressure values placed at 5 points on the insole [15]. Hegde et al. recognized 14 types of daily motions from three pressure sensors (FSR 402) in the insole and an acceleration angular velocity sensor attached to the wrist; however, they used a wrist sensor [16]. Although these studies recognized similar motions, the number or arrangement of sensors were not discussed in detail, and sensors were laid out independently.

In this research, a large number of pressure sensors were spread over the entire sole. In consideration of daily contexts, effective points for measurement were studied.

3. Evaluation

3.1 System Configuration

In this paper, first, we evaluate the accuracy of recognizing postures and gestures by using shoes with many (130 points) pressure sensors to clarify if the foot pressures explain whole body postures and gestures. Second, we investigated the optimal sensing position to realize highly accurate estimation of daily postures and motions with the minimum number of sensors.

In this section, we describe the evaluation environment used to evaluate the accuracy of recognizing postures and motions from foot pressure. **Figure 1** shows the system configuration. To obtain foot pressure data, medilogic's system for measuring the distribution of foot pressure [17] was used. The system acquires about 130 points of pressure values on one foot, for a total of about 260 pressure values, and transmits the data to a PC via Wi-Fi. The sampling rate was set to 100 Hz. Also, video data was acquired by using video cameras to confirm subjects' real motions. All subjects who participated wore running shoes, JOG 100 2 by ASICS, while foot pressure was measured in the experiment described in the next section.

3.2 Experimental Method

In the evaluation experiments, foot pressure data were acquired when the 22 postures and gestures in **Fig. 2** were performed. First, to ascertain whether or not the context of these postures and gestures could be estimated from foot pressure, the recognition accuracy for each context was calculated from foot pressure data when



Numbers are context ID.

Fig. 2 22 kinds of postures and gestures.

Table 1 Subject information.

Subjects	1	2	3	4	5	6	7	8	9	10
Height [cm]	182	157	168	171	170	159	171	154	170	165
BMI	17.8	19.1	18.6	21.9	19.0	21.1	25.3	19.8	19.7	18.0
Shoe Size [cm]	28	23.5	26	27	26	24	27	23.5	26	25
Male/Female	M	F	M	M	M	F	M	F	M	F
Characteristic of legs *1	Straight	O-leg	O-leg	Straight	Straight	Unknown	Straight	Straight	Straight	Straight

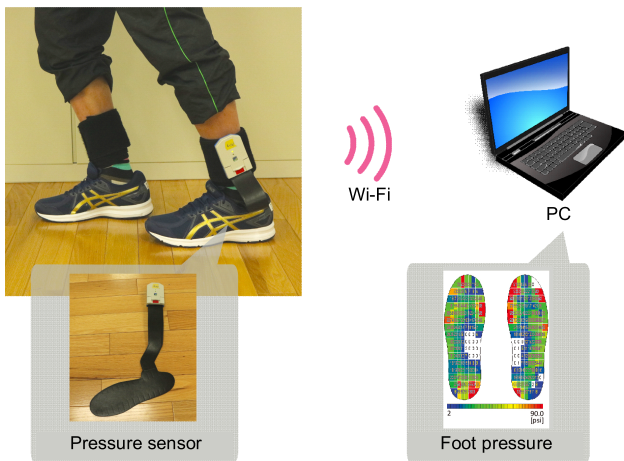


Fig. 1 System configuration.

each motion was taken. In addition, to estimate daily postures and gestures from foot pressure with a high accuracy and with the minimum sensor configuration, the optimal measurement points used to select two points to combine into the best combination were evaluated on a round-robin basis. Using the system described in Section 3.1, foot pressure data were acquired under the assumption of 22 kinds of daily motions, shown in Fig. 2. Ten subjects, 6 men and 4 females, participated. They were in their twenties. **Table 1** shows the subjects' heights, foot sizes, and gender. Also, because there was a possibility that the shape of the legs was related to the pressure of the feet, the subjects were asked to indicate their leg shape characteristic from among five choices, O-leg, X-leg, neither, unknown, and others. Table 1 shows the subjects' answers.

In the experiment, foot pressure data of about 30 seconds were

*1 Characteristic of legs means the response of the subjects from among five choices: O-leg, X-leg, straight, unknown, others.

collected after each posture or motion stabilized, and one set, 22 kinds of motions per one subject, was acquired. Regarding how we decide the 22 kinds of contexts, Bao et al. [18] summarized the contexts recognized in several pieces of conventional research. The contexts were ambulation, posture, typing, talking, bicycling, stairs up & down, shaking hands, writing on board, and arm movement. Furthermore, this paper [18] evaluated 20 kinds of contexts, that is, walking, sitting & relaxing, standing still, watching TV, running, stretching, scrubbing, folding laundry, brushing teeth, riding elevator, walking while carrying items, working on computer, eating or drinking, reading, bicycling, strength-training, vacuuming, lying down & relaxing, climbing stairs, and riding escalator [18]. For our research, we chose actions that can be done when wearing shoes from among these. Regarding postures, we assumed that complicated movements of the arms that are made without trunk twisting or movement were not suitably recognizable from shoes, so we added every posture that included trunk movement that we could think of. For our experiences to review the conventional papers, there are two types of way to decide the target contexts for activity recognition. One is that the paper had clear target application(s) and clearly the target contexts are defined to achieve the requirements on the application. The other is that there was no clear application and the target contexts were selected including various daily/basic activities not to limit the target applications. Our purpose of this research is to establish a general-purpose activity recognition using foot pressure sensors, so our approach is similar to that of the latter one. In conventional papers in the latter case, there was no clear rule/policy of selecting contexts clearly. Therefore, we also selected contexts carefully considering the target contexts in existing works, and it was not a problem as context recognition research.

On the basis of the above, to facilitate comparison with prior research by making our research similar to conventional studies

on recognizing daily motions [4], [6], [18], we adopted as many contexts from the previous pieces of research as possible.

3.3 Evaluation Method

3.3.1 Data Processing before Analysis

Medilogic’s insole for measuring the distribution of foot pressure consists of 130 points for one foot with a foot size of 25 cm or larger and 107 points with a shoe size of smaller than 25 cm. For this research, we assumed a shoe-type system that uses commercially available sensors such as FSR 402 [19]. Each measurement point of medilogic’s insole sensor used in this experiment is smaller than those of FSR 402. Therefore, as shown in Fig. 3, we used the average value of pressure values for every four adjacent pressure sensors as one area for evaluation. In the case of a subject using 25 cm or larger, there were 105 areas per foot for a total of 210 sensors, and in the case of smaller than 25 cm, there were 84 areas per foot for a total of 168 areas for the subsequent evaluation. The area numbers used are shown in Fig. 4.

3.3.2 Evaluation 1: Recognition Accuracy When All Measurement Areas Were Used as Features

As described in Section 3.2, by using all values obtained for each shoe size, the recognition accuracy was evaluated for 22 kinds of contexts. Four recognition algorithms were used: C4.5, random forest, naive Bayes, and support vector machine (SVM). These data were evaluated by 3-fold cross validation using the

data mining tool Weka [20].

A total of 630/504 features were used in Evaluation 1, which were both feet for each of 105/84 areas of instantaneous values, the average values of the past ten samples (0.1 second), and the variance values of the past ten samples (0.1 second) in each of two areas. The average value and variance value were calculated by setting the window size to 10 samples (0.1 second) and sliding the window every sample.

For n samples (x_1, x_2, \dots, x_n) , their average value is \bar{X} , and the variance value (sample variance) used for the feature quantity can be obtained by using the following equation.

$$s^2 = \frac{1}{n} \sum_{i=0}^n (x_i - \bar{X})^2 \tag{1}$$

Classifiers were constructed for each subject and evaluated by using a unique model for each subject.

3.3.3 Evaluation 2: Recognition Accuracy When Combinations of Two Areas Were Used as Features

A combination of two recognition areas for which the recognition accuracy was high was selected on a round-robin basis with the average recognition accuracy. Subjects with shoe sizes of 25 cm or larger wore shoes with 105 separated areas per foot, and subjects of smaller than 25 cm wore them with 84 separated areas per foot. When choosing 2 points from 105 areas, there are 5,460 combinations; similarly, there were 3,486 patterns in the case of 84 areas. For both of these combinations, the recognition accuracy was evaluated with the following procedure. Two areas were selected, and the out-of-bag (OOB) error rate was calculated by using random forest. The same features as Evaluation 1 were used. This procedure was performed for all combinations, and the recognition accuracy was evaluated by comparing the average OOB error rate of the 22 contexts.

Shoes were personalized for each person. The optimum two points were tested by using a model that was unique to each person to determine the ranking of the combination of two points suited to the individual. Comparing the difference in recognition rate of the selected two points with the rate of all of the points, we increased the number to 2 and 3 while calculating recognition accuracies. Therefore, in Evaluation 1 and Evaluation 2, classifiers were constructed for each subject and evaluated by using the subjects’ own models. Assuming that shoes with sensors will be sold on the market, it will be practical for the best two points to be fixed. To evaluate the fixed points, we also conducted two tests using each subjects’ models and the models of others.

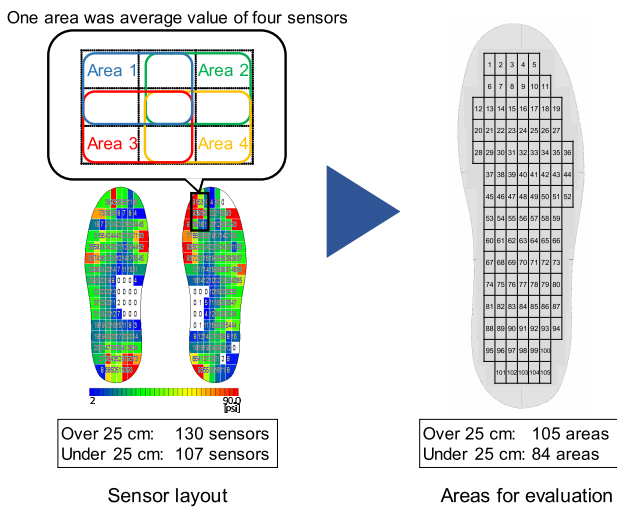


Fig. 3 Areas calculated from foot pressure sensors.

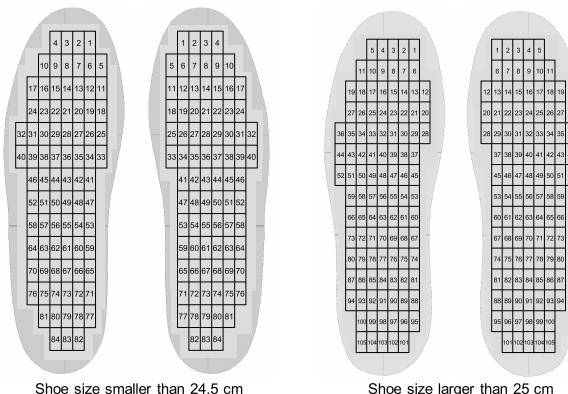


Fig. 4 Calculated area Nos. for evaluating.

Table 2 Recognition rate using all areas of soles.

Subject	Recognition Rates [%] (All Areas)			
	C4.5	Random Forest	Naive Bayes	SVM
1	99.4	99.9	88.9	99.8
2	98.4	99.3	81.5	99.3
3	99.3	99.9	85.5	99.8
4	99.4	99.9	82.0	99.5
5	99.4	99.9	87.7	99.9
6	98.7	99.6	83.1	99.6
7	99.0	99.9	86.6	98.1
8	98.2	99.5	81.8	98.5
9	98.8	99.8	81.1	99.2
10	98.3	99.5	77.6	99.2
Ave.	98.9	99.7	83.6	99.3

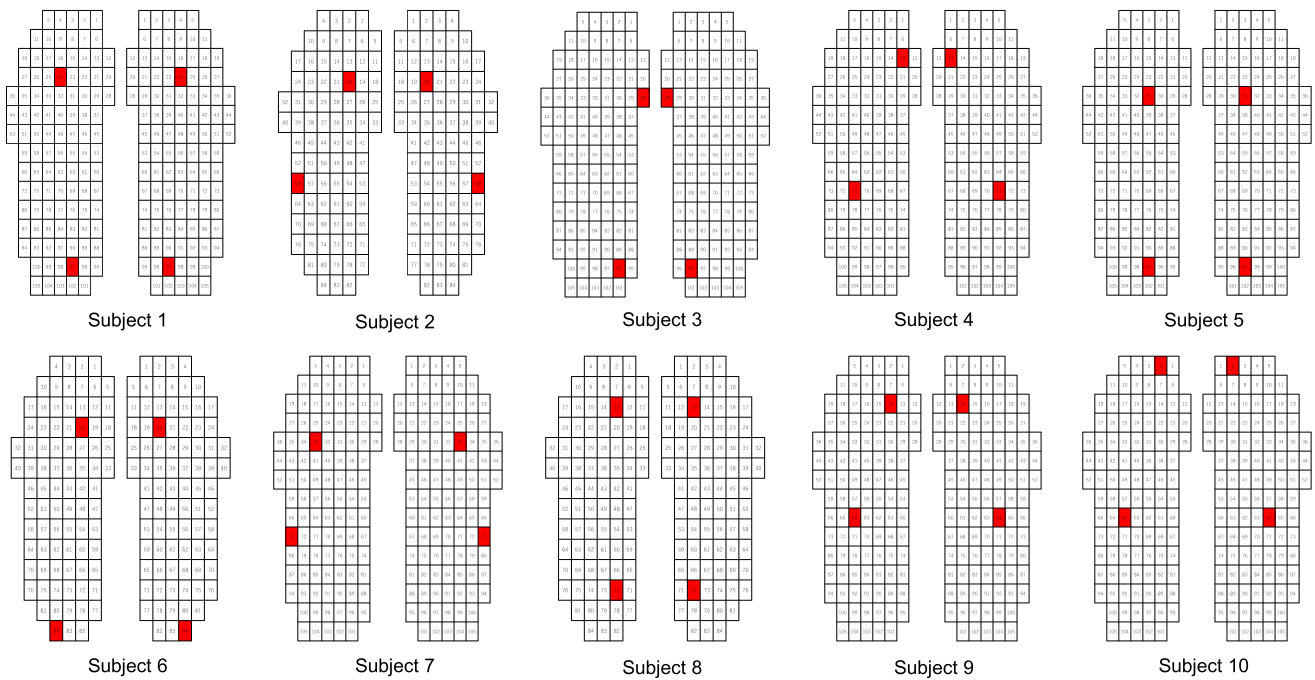


Fig. 5 Best two areas for each subject.

Table 3 Ranking of pressure area combinations.

Ranking	Area combination (Area No.)																			
	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6	Subject 7	Subject 8	Subject 9	Subject 10										
1	24	97	20	58	28	96	13	71	31	97	20	84	33	73	13	72	14	64	2	64
2	23	97	20	57	29	97	14	71	32	101	13	61	21	66	13	66	14	65	1	64
3	23	96	13	58	21	97	12	71	32	102	20	83	20	66	12	70	13	64	14	14
4	24	98	13	57	29	96	12	73	32	97	12	61	32	66	12	72	13	65	2	57
5	24	96	13	56	21	90	12	72	31	98	13	67	21	72	12	69	13	58	22	64

3.4 Result

3.4.1 Result of Evaluation 1

Table 2 shows the motion recognition accuracy for each subject with the feature quantities of all areas. The recognition accuracy for random forest was 99.7%, which was the maximum among the four classifiers. From this result, when all of the foot sole sensors were used, the subjects' motions could be recognized at nearly 100%.

3.4.2 Result of Evaluation 2

The combinations of the two points with the highest average recognition accuracy for each subject are shown in Fig. 5. In addition, the combinations with high average recognition accuracy for each subject in Table 3 are ranked up to the fifth ranking. Furthermore, Table 4 summarizes the minimum error rate, maximum error rate, etc. for the best two points of each subject. In addition to that, the context ranking is also shown in Table 4, arranged in order of increasing recognition accuracy of the contexts for each subject when using the best two points. As shown in Fig. 5, for each subject, the combination of the best two points with the average recognition accuracy of 22 contexts was the first point, that is, the near thenar (thumb ball of foot), which is located near the thumb ball, and the second point, the outside of the middle foot or the heel. One of the two best points was near the thenar for nine out of ten subjects. In comparison, the combinations of two points with the lowest average recognition accuracy were two areas adjacent to the arch for eight subjects. The remaining two persons

(Subjects 1 and 3) had poor recognition accuracies for two adjacent points on the outer edge of the heel and on the outer edge of the toes, respectively. There was no relationship between the best combination and the information on the O-leg and the X-leg in Table 1. Since the motions that could be recognized well for each of the two points were slightly different, it would be best to finely adjust the optimum arrangement of the two points depending on the target motions.

Next, for a practical application, to create a shoe-type device, the places in which the sensors should actually be arranged were investigated. In other words, two common points for which all participants' contexts can be recognized with high accuracy were considered. From Table 4, when we selected the optimum two points for each user, the average recognition accuracy was 94.5%. This result is thought to be in a sufficiently useful range for daily life. However, the results show that the recognition accuracies of gesture contexts were not high. We consider that these low recognition rates are related to fixing the window sizes of the average value and variance value to be as short as 0.1 seconds. This could possibly be improved by adjusting the window size.

In Fig. 6, the coordinates of seven people with sizes of 25 cm or larger and three people with 25 cm or smaller were compared in terms of ratio. The best two points of all subjects were plotted in two-dimensional coordinates with the point of origin on the right foot heel. As shown in Fig. 7, the combination of these two points was divided into two patterns without duplication by using

Table 4 Summary of best combinations of sensor areas.

Subject ID	Best area Nos.		Summary of recognition rate [%]			Context number for recognition rate rank (1: High – 22: Low)																					
	Area 1	Area 2	Min.	Mean	Max.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	24	97	61.1	95.7	100.0	1	2	4	5	6	7	8	9	10	11	13	14	15	18	22	3	12	20	21	19	16	17
2	20	58	44.8	93.7	100.0	1	5	6	7	8	9	10	11	12	13	14	4	3	15	2	21	18	16	19	22	17	20
3	28	96	54.3	94.7	100.0	1	4	5	6	8	9	11	15	22	18	3	7	10	13	14	2	12	21	20	19	17	16
4	13	71	70.1	94.6	100.0	1	4	8	13	14	15	6	10	5	9	7	11	3	18	12	2	22	20	21	16	17	19
5	31	97	52.6	94.0	100.0	1	4	5	6	7	8	9	10	11	12	13	14	15	18	22	2	3	21	19	17	16	20
6	20	84	78.8	97.3	100.0	1	2	4	5	6	7	8	9	10	11	12	14	22	13	18	3	15	21	16	20	19	17
7	33	73	45.3	92.9	100.0	1	3	4	5	6	9	10	11	14	15	7	2	22	12	8	13	18	21	19	16	17	20
8	13	72	62.5	94.9	100.0	4	5	7	8	9	10	11	12	13	14	18	2	1	15	6	3	21	22	20	19	16	17
9	14	64	58.8	93.8	100.0	1	9	11	14	7	10	18	2	12	6	8	15	22	3	5	13	4	21	20	19	16	17
10	2	64	59.9	93.5	100.0	1	4	5	6	7	8	9	15	22	10	13	18	14	11	3	2	12	20	21	19	16	17
Ave.	-	-	58.8	94.5	100.0	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

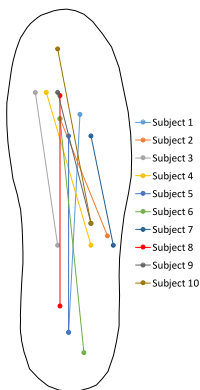
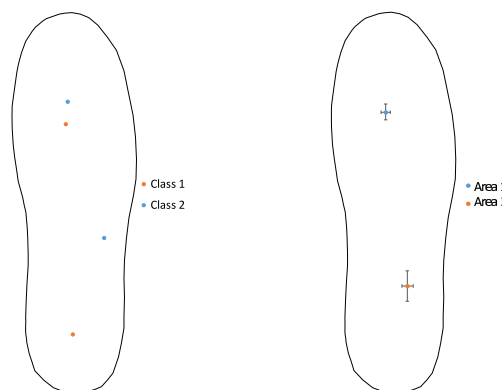


Fig. 6 Plotting best two points on 2D coordinates.



(a) Plotting two patterns for best combinations on 2D coordinates (b) Average of coordinates of best two points

Fig. 8 Summary of best combinations of areas.

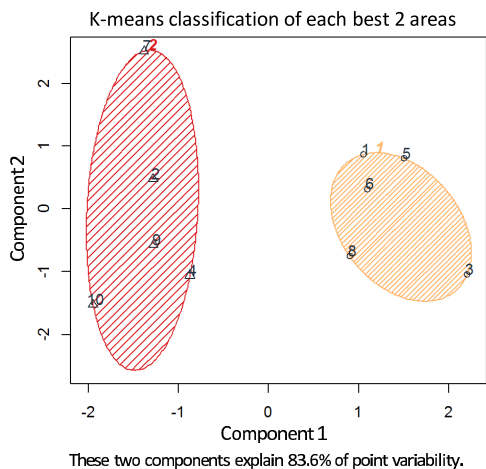


Fig. 7 Patterns of best two points classified by k-means.

the k-means method. Therefore, it can be thought that there were roughly two best combinations, shown in **Fig. 8** (a), for the subjects. That is, one of the two optimum points was commonly the near thenar for the subjects; however, individual differences for the other one point appeared, and two major patterns [Fig. 8 (a)] were observed. Therefore, by taking three points of data and covering these two combinations, it will be possible to cope with individual differences. Furthermore, looking at the two points of Fig. 6, the two points on the anterior half of the sole and around the heel posterior of the arch were commonly selected as the best combination for all subjects. Therefore, the mean value of the coordinates of the anterior and posterior areas of the feet was calculated, and the average coordinates of the best combination for the 10 subjects were calculated. The average of the best points is

shown in Fig. 8 (b). The coordinates in Fig. 8 (b) were area Nos. 23 and 85 of Fig. 4 for subjects with sizes over 25 cm and area Nos. 20 and 68 of Fig. 4 for those smaller than 25 cm.

The recognition accuracy of these points is shown in **Table 5**, and the accuracy was about 91.9% on average. For all subjects, the average recognition accuracy when choosing the optimum two points for each subject was 94.5% from Table 4, and both accuracies were almost the same.

However, since it is doubtful whether the areas should be simply averaged regarding the decision of the two points, we compared the recognition accuracy when using the patterns of the combination of the two best points in Fig. 8 (a) (Class 1, Class 2) to the recognition accuracy when using the average best combination point in Fig. 8 (b). **Table 6** shows the result. From this result, the recognition accuracy of the average best combination was high and confirmed to be almost the same as the two patterns.

Therefore, as a conclusion to the two-point evaluation, when recognizing daily motions as done in this research, the arrangement of Fig. 8 (b) was the combination of the best two points that can be used for recognition with high accuracy while covering individual differences. However, because we did not evaluate putting the shoes on and taking them off in this experiment, we need to investigate this as future work.

3.4.3 Evaluation on Versatility

Up to this chapter, we have investigated the optimal combination of the two points. Two different optimal combinations for two sensors were mainly observed, and nearby the thenars were common to the two patterns. When adapting to commercially

Table 5 Recognition rate of average of best combination areas.

Context No.	Recognition rate [%]										Ave.
	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6	Subject 7	Subject 8	Subject 9	Subject 10	
1	100.0	100.0	100.0	100.0	100.0	100.0	100.0	99.8	100.0	100.0	100.0
2	99.8	100.0	100.0	100.0	98.8	100.0	99.7	100.0	99.5	100.0	99.8
3	99.9	99.9	100.0	99.6	99.7	99.0	100.0	100.0	98.3	99.9	99.6
4	100.0	99.9	100.0	100.0	99.9	100.0	100.0	100.0	67.3	99.4	96.6
5	99.9	100.0	99.9	99.9	100.0	98.4	100.0	100.0	99.8	100.0	99.8
6	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
7	100.0	100.0	100.0	100.0	100.0	99.9	100.0	100.0	100.0	100.0	100.0
8	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
9	100.0	100.0	100.0	99.9	100.0	100.0	100.0	100.0	100.0	100.0	100.0
10	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	99.1	99.9
11	100.0	97.8	100.0	100.0	100.0	100.0	100.0	100.0	100.0	87.9	98.6
12	100.0	99.5	79.1	100.0	99.9	100.0	97.0	100.0	85.7	96.4	95.8
13	100.0	100.0	99.7	100.0	100.0	100.0	68.9	100.0	82.9	100.0	95.2
14	100.0	100.0	100.0	100.0	100.0	99.9	100.0	100.0	100.0	100.0	100.0
15	100.0	100.0	100.0	100.0	99.9	99.9	100.0	100.0	99.8	100.0	100.0
16	82.0	58.0	50.7	61.0	55.3	77.1	63.0	63.5	51.5	43.3	60.5
17	61.4	61.8	52.9	67.9	56.8	67.9	56.9	64.4	57.0	51.4	59.8
18	94.8	75.4	97.1	76.2	82.0	100.0	99.5	100.0	79.6	71.8	87.6
19	79.5	78.7	77.8	56.5	77.7	86.1	70.7	72.3	78.1	50.9	72.8
20	92.3	49.8	87.9	83.3	49.0	79.8	31.3	82.0	69.8	60.9	68.6
21	80.7	98.7	81.5	40.7	98.6	98.5	96.4	96.8	96.1	92.8	88.1
22	100.0	100.0	100.0	99.9	100.0	100.0	100.0	96.7	99.7	99.9	99.6
Ave.	95.0	91.8	92.1	90.2	91.7	95.8	90.2	94.3	89.3	88.8	91.9

Table 6 Comparison of recognition rates of two points.

Sub. No.	1	2	3	4	5	6	7	8	9	10	Ave.
Class No.	1	2	1	2	1	1	2	1	2	2	
Class 1	95.1	91.2	92.6	91.3	92.5	95.7	89.4	93.8	90.8	88.7	92.1
Class 2	91.8	93.6	89.3	92.2	86.9	96	87.8	94	91.9	91.7	91.5
Ave. of all best areas	95.0	91.8	92.1	90.2	91.7	95.8	90.2	94.3	89.3	88.8	91.9

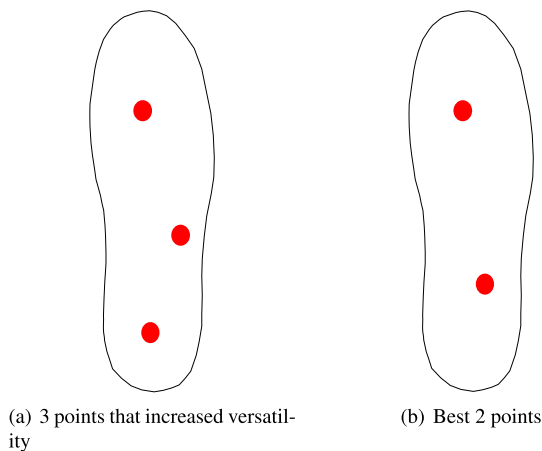


Fig. 9 Best 2 points and 3 points that increased versatility.

available shoes, generalizing the best points is important in order to cope with individual differences. If the shoe device can overcome hardware problems such as power consumption and can take the data of three points, we propose the sensor arrangement shown in Fig. 9 (a). These three points corresponded to individual differences, but it is hypothesized that the best two patterns would have a higher recognition accuracy, and their placement would have more versatility. An evaluation was added as follows. To evaluate the best placement of the two points, we took the approach of finding the best area of an individual and averaging it. The purpose of the three-point evaluation differed from the two-point evaluation. In other words, the three-point evaluation was not an evaluation for finding the best three points for an individual but an evaluation to raise versatility. As in the evaluation of the

two points, the OOB error rate was calculated by using random forest, taking six features as follows. We took the instantaneous value, the average value, and the variance value of the past ten samples (0.1 second) for each selected area of two points. Table 7 shows the result. The average recognition accuracy was 98.4%, which was almost the same as the recognition accuracy when using all of the initial points. Therefore, when three-point data are taken and cover these two patterns, it will be possible to cope with individual differences.

3.4.4 Evaluation by Training with Other People’s Data

To confirm recognition accuracies when training with other people’s data, we calculated the recognition rates when training with others’ data. Nine of the ten people’s data were used as training data. The algorithm used to generate a model was random forest. Then, the data of the remaining person were tested by using the model. The evaluation was conducted for each of the ten subjects, and the recognition accuracy was calculated.

Tables 8 and 9 show the recognition rates of the 22 contexts for each subject. The average recognition accuracy (F-value) of all subjects was 36.4% for the two points in Fig. 9 (a) and 38.5% for the three points in Fig. 9 (b). The recognition accuracy of each subject was less than 50%. On the basis of these results, we conclude that the recognition accuracy with others’ training data was low. Therefore, we believe that it is necessary to train with one’s own data.

3.4.5 Discussion

The accuracy in recognizing contexts as was similarly done in the previous research was high overall this time. The movements of the upper body could be recognized by obtaining those

Table 7 Recognition rate of a combination of 3 areas with high versatility.

Context No.	Recognition rate [%]										Ave.	
	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6	Subject 7	Subject 8	Subject 9	Subject 10		
1	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
2	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
3	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
4	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
5	100.0	100.0	100.0	99.9	100.0	100.0	100.0	100.0	100.0	99.9	100.0	100.0
6	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
7	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
8	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
9	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
10	100.0	99.9	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
11	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	99.7	100.0
12	100.0	100.0	85.9	100.0	100.0	100.0	95.4	100.0	100.0	99.4	98.1	98.1
13	100.0	100.0	99.2	100.0	100.0	100.0	98.9	100.0	100.0	100.0	99.8	99.8
14	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
15	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
16	97.9	95.5	94.0	97.0	97.1	89.3	91.3	90.7	93.2	82.1	92.8	92.8
17	96.4	96.6	92.4	96.7	95.8	89.2	90.6	86.2	89.9	88.1	92.2	92.2
18	100.0	97.5	100.0	97.6	100.0	100.0	100.0	100.0	93.6	93.8	98.2	98.2
19	98.9	97.5	98.3	98.6	98.2	97.9	98.2	97.0	97.0	89.0	97.1	97.1
20	98.9	85.3	97.6	97.1	99.2	80.1	78.6	91.1	95.7	90.7	91.4	91.4
21	99.7	99.5	99.9	81.2	99.9	99.9	99.0	100.0	99.4	99.3	97.8	97.8
22	99.9	87.1	100.0	99.8	100.0	100.0	100.0	98.7	99.8	100.0	98.5	98.5
Ave.	99.6	98.1	98.5	98.5	99.6	98.0	97.8	98.4	98.6	97.4	98.4	98.4

Table 8 Evaluation result of 2 fixed areas using a model of others.

Context No.	Recognition rate [%]										Ave.	
	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6	Subject 7	Subject 8	Subject 9	Subject 10		
1	0.8	2.1	0.5	0.2	0.2	77.6	26.5	0.5	10.2	0.5	11.9	11.9
2	65.0	88.7	70.1	67.8	35.4	76.1	65.9	81.8	91.7	74.6	71.7	71.7
3	69.4	87.4	50.8	48.5	19.8	75.2	60.0	93.8	59.8	85.0	65.0	65.0
4	0.4	92.6	35.0	20.8	0.0	62.2	11.1	53.8	97.3	0.2	37.3	37.3
5	93.1	21.1	9.4	55.9	0.0	0.1	2.2	85.3	1.8	0.0	26.9	26.9
6	0.0	0.0	5.0	0.0	14.9	0.0	29.7	0.0	27.9	0.0	7.7	7.7
7	96.9	17.7	36.4	0.0	0.2	4.6	34.2	0.1	9.5	0.8	20.0	20.0
8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	10.1	0.0	0.0	1.0	1.0
9	0.0	0.0	0.0	0.0	96.9	88.1	0.0	0.0	0.0	98.3	28.3	28.3
10	4.7	29.2	1.6	14.5	0.0	78.8	54.0	56.6	56.5	62.0	35.8	35.8
11	0.0	0.0	0.0	0.0	9.0	7.9	0.0	0.0	0.0	8.4	2.5	2.5
12	97.9	68.0	97.2	90.8	66.3	68.2	60.9	82.9	87.4	54.3	77.4	77.4
13	0.0	17.9	0.0	0.0	37.5	35.8	0.0	0.0	0.0	1.2	9.2	9.2
14	56.4	86.3	0.0	0.0	44.9	51.4	0.5	0.1	7.9	9.8	25.7	25.7
15	0.0	84.3	0.0	0.0	97.4	96.8	22.4	68.7	37.6	0.0	40.7	40.7
16	30.5	40.3	49.6	41.5	36.1	30.9	33.2	28.5	39.9	24.1	35.5	35.5
17	27.2	47.1	42.9	30.9	31.9	43.7	36.5	27.1	25.2	27.0	34.0	34.0
18	34.4	55.4	44.4	60.2	50.1	35.6	53.3	36.6	57.7	29.5	45.7	45.7
19	46.1	58.8	42.9	39.0	30.0	41.7	21.3	60.7	42.0	38.2	42.1	42.1
20	25.1	54.2	23.7	9.5	10.5	31.8	46.8	23.4	44.0	39.5	30.9	30.9
21	56.7	78.5	52.3	85.5	57.6	84.2	75.0	85.0	79.7	82.1	73.7	73.7
22	86.2	72.2	78.3	87.9	11.7	89.1	87.4	88.4	94.0	87.1	78.2	78.2
Ave.	36.0	45.5	29.1	29.7	29.6	49.1	32.8	40.2	39.5	32.8	36.4	36.4

affecting the balance of the lower body. Also, because it was assumed that shoes are being worn in this research, depending on the cultural sphere, other approaches would be more versatile if the target contexts are inside the house. Also, the recognition accuracy would be higher than that of other research [18] if easily recognizable contexts such as simple walking and running were used. However, since Ref. [18] used a semi-naturalistic environment, it would be difficult to compare this point in terms of recognition accuracy. Compared with other approaches, we consider that the content of this research would be particularly suitable for recognizing static postural changes due to left and right balance difference and changes in the trunk center of gravity, which has not been done before with other approaches. When trying to recognize all 22 contexts, the recognition accuracy was low for walking, walking around inside (left), and walking around inside

(right). The recognition accuracy is greatly influenced by the selection of contexts, so there are actions that are worth evaluating with some sort of selection, for example, we added escalators, elevators, opening and closing the door, cleaning, and walking around inside (left and right).

As a wearable device that records daily activities, the Fore-Athlete 935 smartwatch [21] can recognize the number of steps, activity level, sleep state, heart rate, and GPS and analyze running by using an acceleration device attached to the waist that works with the watch. Sony's Lifelog [22] can log walking/running, bicycles, cars, sleeping hours, and mobile operating time. While these obtain physiological information such as a sleeping state and the heart rate, we cannot obtain static postural changes with the load balanced on the left or right as in this research.

As for the wearing costs, most of wearable devices including

Table 9 Evaluation result of 3 fixed areas using a model of others.

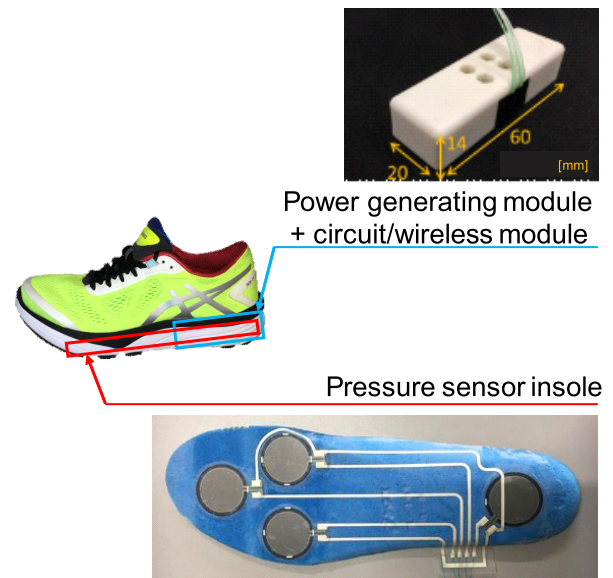
Context No.	Recognition rate [%]										Ave.
	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6	Subject 7	Subject 8	Subject 9	Subject 10	
1	0.5	0.2	0.5	0.3	0.2	0.4	1.8	0.4	0.4	0.5	0.5
2	73.9	97.9	88.9	93.4	81.3	98.0	62.5	92.4	54.6	97.1	84.0
3	81.9	0.0	52.3	93.9	33.4	77.3	88.7	92.0	74.4	92.7	68.7
4	0.3	29.1	94.0	3.7	0.2	98.4	0.0	5.2	1.2	0.2	23.2
5	66.6	16.8	0.7	16.9	0.1	5.3	0.0	0.0	68.2	57.4	23.2
6	0.0	22.4	4.0	0.0	13.8	3.0	16.6	0.0	1.5	1.0	6.2
7	0.0	0.0	0.0	0.0	0.1	0.0	9.4	0.0	5.5	27.5	4.2
8	92.1	0.1	88.6	0.0	72.2	99.9	0.0	0.0	0.0	0.9	35.4
9	99.8	0.0	21.1	51.7	99.9	99.1	0.0	0.0	0.0	78.1	45.0
10	23.7	16.2	82.0	0.0	95.8	78.4	32.9	80.0	71.2	74.1	55.4
11	6.7	0.0	1.0	8.2	0.0	8.4	0.0	0.0	0.0	5.6	3.0
12	92.0	70.8	80.9	97.3	59.4	50.2	62.2	88.4	97.5	61.4	76.0
13	0.0	23.3	99.9	0.0	17.7	16.3	0.0	9.8	0.0	31.2	19.8
14	5.1	37.5	0.0	0.0	0.2	1.6	0.0	0.0	18.6	0.1	6.3
15	0.0	60.4	61.3	0.0	77.0	0.1	0.6	86.4	38.2	37.0	36.1
16	63.2	51.3	70.4	49.7	47.2	47.8	34.3	9.3	43.2	29.8	44.6
17	53.8	51.3	53.0	43.2	20.6	34.2	30.7	32.8	30.3	40.9	39.1
18	34.0	36.1	34.5	74.4	63.4	56.0	64.6	19.7	69.7	46.9	49.9
19	40.2	64.9	35.6	45.0	44.0	41.1	20.5	22.0	33.6	37.6	38.4
20	44.3	39.8	34.1	6.4	7.9	26.1	40.2	32.9	60.1	51.1	34.3
21	59.1	76.5	57.1	88.6	50.9	83.1	76.5	80.1	85.5	84.8	74.2
22	93.9	71.5	76.8	86.6	10.9	93.9	96.5	83.9	96.0	93.0	80.3
Ave.	42.3	34.8	47.1	34.5	36.2	46.3	29.0	33.4	38.6	43.1	38.5

smart watches and an activity tracker, the devices are “additional” devices. It means that users do not wear devices depending on his/her mind. On the other hand, everyone wears shoes outdoors and it means that all data outdoors can be collected if all shoes have the function we proposed. Conversely, especially in Japan, since shoes are removed indoors, our system cannot collect any data indoors without using slipper-shaped devices.

In this research, the subjects in the experiment were men and women who were healthy, had a general body shape, and were in their twenties. The results of this experiment are effective for both males and females within the range of those with an average body shape and high ability to walk. If the subjects had balance that was greatly degraded due to aging, injury, etc., it is possible that the results of this experiment, which involved items related to left and right bias, may have been totally different. Regarding the difference depending on the type of shoes, this evaluation adopted sports shoes that are also often used for everyday uses, and only one type of shoe was used with the model. In conventional research, many shoe-type systems adopt sneakers such as sports shoes. However, if the hardness of the sole is different, the way of applying the landing pressure changes, so it is considered that the results of this research may differ from the best arrangement when putting pressure sensors on business shoes etc.

4. Example Application

Applying the results of this research, our research group developed the two shoe-type devices shown in **Figs. 10** and **11**. The first device developed is shown in Fig. 10. Pressure sensors were placed at four points on one foot, and the pressure sensor values at the four points were transmitted to a mobile phone or laptop PC over a BLE connection. The device has a piezoelectric power generation module, so it is battery-free. To select these four points, we chose a total of three points near the thumb ball, the anterior external side, and near the heel. For convenience of wiring, the points of the anterior external side were slightly dif-

**Fig. 10** Developed battery-free shoe device.

ferent from the best points sought for in Section 3. In addition, the maximum number of points without a battery was four. The last one point was placed on the toes because it was more able to acquire additional foot information. In future work, we will improve the sensor arrangement of the prototype shoes to be closer to the result of this research. In addition, we are planning to develop a software that selects motions from the 22 postures and motions acquired from the evaluation experiments in this paper and that recognizes and records motions.

The other device we developed is shown in Fig. 11. Applying the foot pressure analysis of the proposed method, we implemented this shoe-type device, which controls the RGB balance of LEDs according to foot pressure values in real time. The pressure sensors, FSR-402 [19], were arranged at three points on one foot, as shown in Fig. 8. The RGB values of the attached LEDs were controlled by using 256 levels from pressure sensor values, and

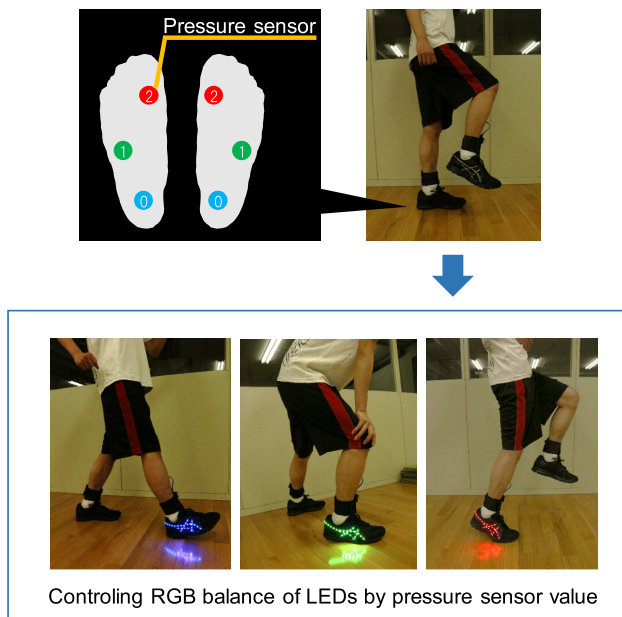


Fig. 11 Developed LED shoe device.

the values were transmitted to an Arduino Nano. The device feeds back a user's foot pressure balance and the magnitude of the values in real time. The arrangement of these pressure sensors was set by using the best arrangement shown in Fig. 9 (a). These shoes can feed back the balance of foot pressure in real time with the LED lights to the user and surrounding people. Therefore, they can be used for sports or walking training. In the future, we will incorporate posture recognition into this device and evaluate the recognition accuracy. In addition, in the evaluations of Section 3, since we evaluated two points symmetrical to the left and right lines on a round-robin basis, we will investigate the difference in foot pressure between the right and left feet. Regarding the sensor placement, it is necessary to adjust the placement again on the basis of the results of this research. However, this study shows that there is a possibility that the motion can be recognized in the future in such a system and that this arrangement can accurately recognize daily motions.

4.1 Directions for Future Work

We are interested in the research directions described below.

4.1.1 Health Care

Shoes are routinely worn when going out. In this study, since we evaluated whether postures and gestures can be recognized with high accuracy from the sole pressure, life logs could be one application, for example, recognizing walking, standing, sitting, unsteady gait, unbalanced loading etc. from foot pressure, always recording it, and using it for health care.

4.1.2 Jogging or Walking Management

By taking foot pressures over a long period of time, we think that it is possible to predict signs of injury from foot pressure balance, pace, and tempo during running. In the same way as jogging management, we think that signs indicating falling when walking could be used for prediction. This could be applied to a system for preventing the elderly from falling over.

The battery-free pressure sensing shoes shown in Fig. 10 re-

quire users to only wear shoes. There is no need to switch them on or charge them as the shoes can keep measuring foot pressure while being worn. Such a device would not force users to perform any extra operations, so it would be easy for users unfamiliar with such devices, for example, the elderly. However, because the shoes are battery-free, there is a limit to the available power. Under these conditions, it is effective to arrange a few sensors at the optimal positions revealed in this research. The shoes are safe because small batteries are not built into them, so shoes can strongly hit the ground, which otherwise could cause batteries to explode.

5. Conclusion

5.1 Contribution

Various shoe-type devices for measuring foot pressure have been developed, but there were no discussions on the optimal measurement points on the human soles. If pressure sensors can be configured with a minimal number of areas with good performance, the power consumption could be reduced while maintaining the recognition accuracy because the number of sensors would be reduced. For shoe-type devices worn for a long time, it is important that the power consumption is low. In this research, the best combinations of two or three points were extracted in consideration of individual differences. This contributes fundamentally to the overall research on support systems that measure foot pressure.

5.2 Conclusion

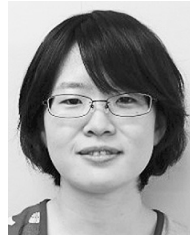
In this study, the recognition accuracies of 22 kinds of daily postures and motions were evaluated from foot-pressure sensor values. Furthermore, by evaluating combinations of two foot-pressure measurement areas on a round-robin basis, the optimum measurement points for high recognition accuracy were examined. As a result, although little individual difference was seen, subjects were largely divided into two major patterns. Among two points that were chosen, combinations of near the thenar and near the heel or a point of the outside of the middle of the foot were highly recognized. When we selected the optimum two points for each subject, the recognition accuracy was about 94.5%, which is considered to be sufficiently useful in daily life. One of the two optimum points was commonly near the thenar for subjects; however, individual differences in the other one point appeared, so two major patterns were observed. By taking three points of data and covering these two patterns, it will be possible to cope with individual differences. The recognition accuracy of averaged combinations of the best two combinations of all subjects was classified with an accuracy of about 91.9% on average. As a result of an evaluation to raise versatility, the average recognition accuracy in a three-point evaluation was 98.4%, which was almost the same as the recognition accuracy when using all of the initial points. Therefore, as a conclusion to this paper, when recognizing everyday motions as used in this research, the arrangement of Fig. 9 was the combination of two or three points for which recognition was possible with high accuracy while covering individual differences. Applying the results of this research, our research group developed two shoe-type devices. One had a

piezoelectric power generation module; thus, it was battery-free. The other controls the RGB balance of LEDs by using foot pressure values in real time. In future work, we plan to develop a software that selects motions from the 22 postures and gestures acquired from the evaluation experiments in this paper and that recognizes and records motions.

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Ayumi Ohnishi received B.Eng. degree from Kobe University in 2014 and M.Env. degree from The University of Tokyo in 2016. She is currently a Ph.D. student at Graduate School of Engineering, Kobe University. Her research interest is wearable computing and ubiquitous computing. She is a student member of the IPSJ.



Tsutomu Terada is a Professor at Graduate School of Engineering, Kobe University. He received B.Eng., M.Eng. and Ph.D. degrees from Osaka University in 1997, 1999, and 2003, respectively. Dr. Terada is currently working on wearable computing, ubiquitous computing, entertainment computing technologies. He is a member of ACM and IEEE.



Masahiko Tsukamoto is a Professor at Graduate School of Engineering, Kobe University. He received B.Eng., M.Eng. and Ph.D. degrees from Kyoto University in 1987, 1989, and 1994, respectively. He is currently investigating wearable computing and ubiquitous computing. He is a member of eight learned societies, including ACM and IEEE.