Estimation of Sidewalk Surface Condition with Insole Devices

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***Abstract*—Pedestrian accidents caused by sidewalk surface conditions have become a problem. Especially, snowy and icy sidewalk surfaces in winter increase the risk of accidents for pedestrians. One simple approach to prevent such accidents is to collect and share information about sidewalk surface conditions with pedestrians. In this study, we present a sidewalk surface condition estimation method. The surface condition estimation method uses an insole device to collect the difference in the pressure distribution at the bottom of the feet during walking to estimate the sidewalk surface condition with a supervised learning model. We collected foot pressure data on four types of road conditions, i.e., asphalt, icy, snowy, and foot-packed snow, and evaluated the estimation performance of the proposed method. The experimental evaluation showed that the proposed method successfully estimated surface conditions with an F-measure of more than 0.9 for six subjects. We also validated the estimation performance with a limited amount of training data and confirmed that 15-step training data resulted in the estimation with an F-measure of more than 0.9.**

***Index Terms*—Insole pressure sensor, slippery sidewalk, limited training data.**

I. Introduction

There is an increasing concern that slippery roads cause pedestrian accidents [1]. Especially, snowy and icy sidewalk surfaces in winter increase the risk of accidents.

For safe walking, pedestrians should know the sidewalk surface conditions and change their walking style for the surface condition, which reduces the risk of accidents. The sidewalk surface condition changes from time to time depending on the weather conditions including temperature and the degree of exposure to sunlight. A sidewalk surface condition sharing system is therefore required to help pedestrians know the surface condition in real time.

Sidewalk surface conditions can be estimated with existing approaches using acoustic [2, 3], image [4, 5], and inertial sensor data [6–9]. However, these approaches are far from practical use due to restrictions on sensor device location, influence from vehicles, or influence of weather conditions. These approaches rely on a special sensor worn by pedestrians, which makes the approaches impractical.

In this study, foot pressure data derived from a limited number of sensors on our newly developed insole device is used to estimate sidewalk surface conditions. We use foot pressure, i.e., the pressure distribution at the bottom of the feet during walking, and estimate surface conditions with a supervised learning model. When we walk on a sidewalk with different surface conditions, the walking style and the ground contact point might be changed, which results in a difference in foot pressure. We utilize the changes to estimate the surface condition.

Although our approach also relies on a special device, insole pressure sensing with a limited number of sensors will be practical. Recently, smart shoes equipped with sensors have been developed, which enable us to acquire information such as movement of the feet [10–12]. We believe that smart shoes are commonly used in our daily lives in the near future.

We asked six subjects to walk on four types of surface conditions, i.e., asphalt, icy, snowy, and foot-packed snow on different days and collected foot pressure data, evaluating the performance of our proposed surface condition estimation method. The experimental evaluation showed that our surface condition estimation method using an individual learning model successfully estimated sidewalk surface conditions with a limited amount of training data. We also confirmed that the high estimation performance with a limited number of insole pressure sensors.

Specifically, our main contributions are threefold:

- We present a sidewalk surface condition estimation method that relies on a newly developed insole device equipped with a limited number of pressure sensors.
- We show the estimation performance with an F-measure of more than 0.9 even if we use 15-step data for the supervised learning model training.
- We show the estimation performance with an F-measure of more than 0.9 with a limited number of sensors on the insole device.

The remainder of the paper is organized as follows. Section II looks through related work on the estimation method

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of sidewalk surface conditions and on foot-pressure-related sensing. We present our proposed method in Sect. III, followed by evaluations in Sect. IV. Section V concludes the paper.

II. Related Work

A. Sidewalk Surface Condition Estimation

In the field of sidewalk surface condition estimation, many studies utilize sensor data from mobile devices worn by pedestrians [2–9, 13, 14]. In acoustic approaches [2, 3], the estimation accuracy is highly affected by vehicle running and clothing rubbing noises, which is critical for sensing on sidewalks. Image-based approaches [6, 7] also suffer from lighting condition, which changes by the time of day and weather conditions. Answer approach is to use inertial sensor data acquired from a smartphone worn by people or from devices attached to their shoes [6–9]. However, smartphones are required to be installed in a specific position such as pants pocket [6, 7] and on-shoes [8, 9], which makes the approaches impractical. The on-shoes sensor approach also faces difficulties in estimation on flat sidewalk conditions such as asphalt and snowy surfaces.

The method using foot pressure data for sidewalk surface condition estimation can be found in Refs [13, 14]. Matthis et al. estimated sidewalk surface conditions using insoles fitted with pressure sensors [13]. The foot pressure data were used to estimate six different sidewalk surface conditions: gravel, grass, paving stones, carpet, and tartan. Kuzume et al. proposed a method to classify Braille blocks using pressure sensors attached to the soles of feet [14]. This study shows that the values obtained from the pressure sensors can be used to classify the following conditions: nothing stepped on, flat, warning block, and guiding block.

Although the methods presented in these studies have successfully estimated surface conditions, these methods use much sensor information, which makes the methods impractical. We believe that reducing the number of sensors required to estimate surface conditions is important to realize a practical surface condition estimation method. Data collection with specific shoes and at a specific walking pace also makes it difficult to collect training data. The number of people who cooperate to provide foot pressure sensor data with the correct label is likely to be very limited in a practical situation.

B. Foot-Pressure Related Sensing

Foot pressure is used for person identification and activity recognition.

References [15–17] presented person identification using foot pressure. Wada et al. and Zhou et al. have presented person identification methods based on footprint [15] or pressure changes [16] using carpet-type pressure sensor sheets. Sousa et al. used acceleration data derived from an inertial sensor and footprint derived from a capacitive fiber sensor, both placed under the floor, to identify individuals [17]. These studies show that there is a difference in individual walking movements.

References [18–20] presented activity recognition methods using foot pressure. Gonzalez et al. focuses on daily walking movements and recognized behaviors such as forward, turning, backward, and side walking [18]. Moufawd et al. used inertial sensors and insole pressure sensors to recognize three activities: sitting, standing, and walking [19]. Ohnishi et al. recognized 22 everyday postural and gestural behaviors using foot pressure sensors [20]. In these studies, activity recognition is based on changes in foot pressure during each activity. These studies confirm that a variety of information can be collected from changes in foot pressure.

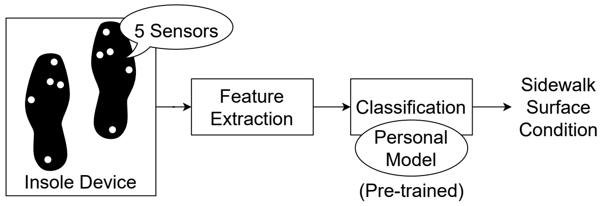


Fig. 1. Overview of the proposed sidewalk surface condition estimation method

III. Sidewalk Condition Estimation Method

A. Overview

Figure 1 shows the overview of the proposed sidewalk surface condition estimation method. The sidewalk surface condition estimation method is composed of three components: insole device, feature extraction block, and classification block. Foot pressure data is derived from insole devices installed inside a pair of shoes. The feature extraction block divides the pressure data with fixed-length windows and extracts features for each window. The classification block finally estimates the sidewalk surface condition for each windowed data using a supervised learning model. We assume that the learning model is trained in advance with pressure data with correct labels.

The following subsections describe the details of each component.

B. Insole Device

Figures 2 and 3 show the developed insole device and the location of pressure sensors on the insole device, respectively. The insole device is equipped with resistive pressure sensors FSR402 on the back of the insole. The pressure sensors are attached at the toe, thenar, root, hypothenar, and heel, as shown in Fig. 3. The pressure sensors have a thickness of 0.25 to 1.25 mm and have a pressure-sensitive range of 0.2 to 20 N. Each sensor is connected to the Arduino with a jump wire and is pulled up to the supply voltage with an Arduino's internal register. A higher sensor value indicates lower pressure.

C. Feature Extraction

The feature extraction block extracts features over fixed-sized windows. We used 5-second sliding windows with an overlap rate of 50%.

We calculate features over all the samples in the window and over the samples corresponding to steps, i.e., while the

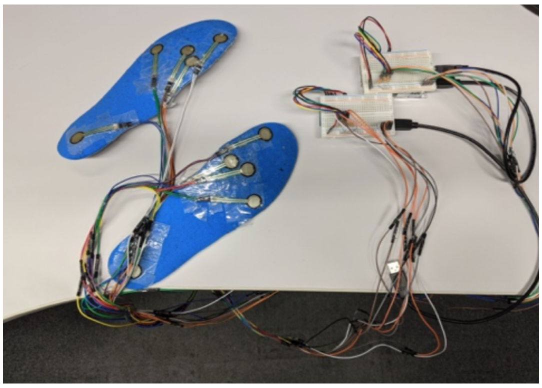


Fig. 2. Insole device

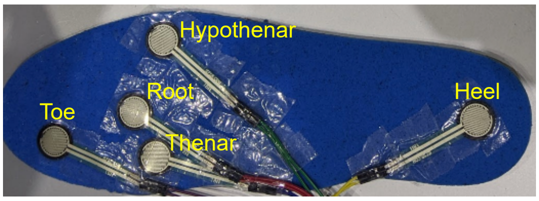


Fig. 3. Pressure sensor location

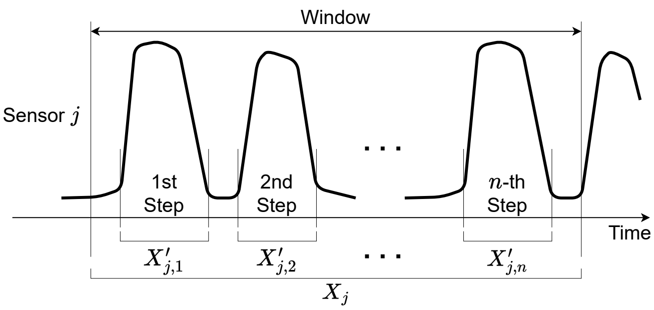


Fig. 4. Notations for feature extraction

foot is on the ground. Figure 4 shows the notations for feature extraction process. A sequence of pressure data samples derived from sensor j in the window is denoted by X_j. We estimate the step timing for each of left and right feet and extract the sensor data samples corresponding to each step. We denote a sequence of the extracted sensor data samples corresponding to n-th step by $X'_{j,n}$.

Step timing is estimated from pressure data X_j. One *step* is defined as the period from the time the foot touches the ground to the time the foot leaves the ground. We assume that the foot is on the ground when toe, heel, and thenar pressures are all above specific thresholds. The thresholds are determined via preliminary experiments. Note that an low-pass filter (LPF) is applied prior to step-timing estimation to reduce the influence of measurement circuit noise.

Six features below are calculated using pressure sensor data samples derived from sensor $j \in S_{left} \cup S_{right}$, where S_{left} and S_{right} are sets of sensors attached to left and right insoles, respectively.

1) w_ave: w_ave is the mean pressure within the window. The mean pressure is calculated for each sensor $j \in S_{left} \cup S_{right}$:

$$w\_ave_j = \mathrm{ave}(X_j), \tag{1}$$

where ave( ) represents the mean of elements in the sequence.

The mean pressure difference between left and right sensors are also calculated for each of sensor locations. Let S_l be a set of sensors attached to location $l \in L = \{toe, thenar, root, hypothenar, heel\}$. The mean pressure difference is calculated as:

$$w\_ave_l = \mathrm{ave}\left(\left\{x \in \bigcup_j X_j \,\middle|\, j \in S_l \cap S_{left}\right\} - \left\{x \in \bigcup_j X_j \,\middle|\, j \in S_l \cap S_{right}\right\}\right), \tag{2}$$

where $A - B$ for sequences A and B represents element-wise subtraction.

We have 10 sensors attached at 5 locations. The total number of w_ave features is therefore 15.

2) w_std: w_std is the standard deviation of pressure data within the window. Let std( ) represent the standard deviation of elements in the sequence. We can calculate w_std in the same manner as w_ave for sensor $j \in S_{left} \cup S_{right}$ and for sensor location $l \in L = \{toe, thenar, root, hypothenar, heel\}$:

$$w\_std_j = \mathrm{std}(X_j) \tag{3}$$

$$w\_std_l = \mathrm{std}\left(\left\{x \in \bigcup_j X_j \,\middle|\, j \in S_l \cap S_{left}\right\} - \left\{x \in \bigcup_j X_j \,\middle|\, j \in S_l \cap S_{right}\right\}\right). \tag{4}$$

The total number of w_std features is 15.

3) step_count: $step\_count$ is the number of steps within the window.

We derive $step\_count$ for each of left and right foot. The total number of $step\_count$ features is therefore 2.

4) step_ave: $step\_ave$ is the mean of statistics of pressure data with foot ground contact. To calculate $step\_ave$, we first calculate basic statistics over $X'_{j,k}$ for each step. We use six basic statistics: mean, standard deviation, minimum, median, kurtosis, and skewness. Let opr( ) represent any of the statistic calculation operations. Any statistic for sensor j and for k-th step is calculated as $\mathrm{opr}\left(X'_{j,k}\right)$. We therefore derive $step\_ave$ for sensor j and for the operation opr as:

$$step\_ave_{j,\mathrm{opr}} = \mathrm{ave}\left(\left\{\mathrm{opr}\left(X'_{j,k}\right) \middle| k = 1, \cdots, step\_count\right\}\right), \tag{5}$$

There are 6 statistics and 5 sensors on both left and right feet. The total number of $step\_ave$ features is therefore 60.

5) $step\_std$: $step\_std$ is the standard deviation of pressure data with foot ground contact. We can calculate $step\_std$ in the same manner as $step\_ave$:

$$step\_std_{j,\mathrm{opr}} = \mathrm{std}\left(\left\{\mathrm{opr}\left(X'_{j,k}\right) \,\middle|\, k = 1, \cdots, step\_count\right\}\right). \quad (6)$$

The total number of $step\_std$ features is 60.

6) $step\_dtw$: $step\_dtw$ is the dynamic time warping (DTW) distance between left and right pressure data. Left and right step timings are different because we use our left and right legs alternately when we walk. We use the DTW distance to reduce the impact of left/right timing difference.

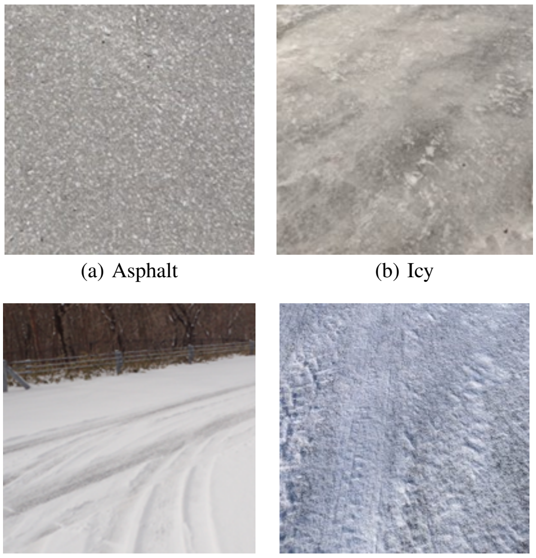
Let $\mathrm{dtw}(A, B)$ represent the DTW distance between sequences A and B. We calculate $step\_dtw$ for sensor location l as:

$$step\_dtw_l = \mathrm{dtw}\left(\left\{x \in \bigcup_j X_j \,\middle|\, j \in S_l \cap S_{left}\right\}, \left\{x \in \bigcup_j X_j \,\middle|\, j \in S_l \cap S_{right}\right\}\right). \quad (7)$$

The total number of $step\_dtw$ features is 5 as we attach a sensor at 5 locations.

D. Classification

The classification block estimates the sidewalk surface condition using a supervised learning model. The supervised learning model is trained for each individual in advance with the features extracted in the feature extraction block. We don't limit the machine learning algorithm. In this paper, we use a linear support vector machine (SVM) classifier.



(a) Asphalt (b) Icy

(c) Snowy (d) Foot-packed snow

Fig. 5. Sidewalk surface conditions to be estimated

Fig. 6. Data collection setup

IV. Evaluation

A. Experiment Setup

We conducted a series of experiments to evaluate the performance of our proposed sidewalk surface condition estimation method. We first evaluate estimation performance with an F-measure when a learning model is built with data derived from a limited number of sensors. Estimation performance using a learning model trained with a limited amount of data, i.e., sensor data corresponding to a limited number of steps, is then evaluated.

B. Sidewalk Surface Estimation Performance

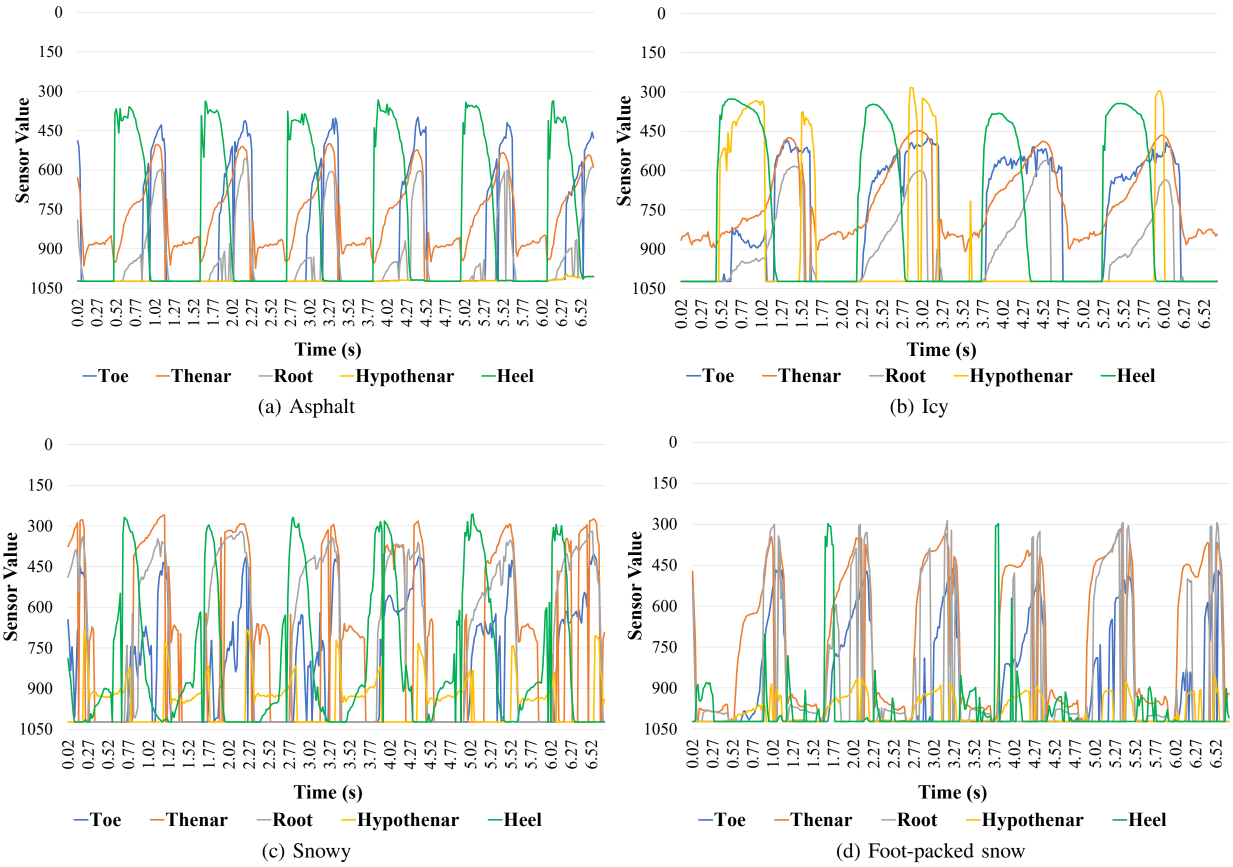
Figure 5 shows the estimation target conditions of the sidewalk surface. In this experiment, we focus on four surface conditions: asphalt, icy, snowy, and foot-packed snow. The icy sidewalk is the sidewalk covered by frozen melted snow caused by temperature changes. The snowy sidewalk is the sidewalk covered by snow immediately after a snowfall. The foot-packed snow represents snow trodden hard by pedestrians.

We recruited six subjects for this experiment. Table I shows the subjects' information. In this experiment, subjects used their own shoes. Their shoe size was 26.0–27.0 centimeters in Japanese shoe size. All subjects were males in their 20s. Four of the six subjects have grown in a snowing area in Japan, who, we believe, are familiar with walking on icy road surfaces.

Figure 6 shows the experiment setup. We ask subjects to walk on a sidewalk with their shoes equipped with insole devices on both feet. Subjects carried a laptop used for power supply and data collection from the insole devices while they walked on the sidewalk. For each sidewalk condition, we collected pressure data for 450 seconds at the sampling rate of 60 Hz while subjects were walking. Note that we gave no instruction on walking style such as walking speed. We collected pressure data for each surface and for each subject on different days and times. There were 179 windows for each surface condition and for each subject as we used 5-second windows with a 50% overlap.

C. Performance with Combination of Sensor Data

To evaluate the surface estimation performance, we estimated a surface condition for each window and calculated a macro F-measure. Table II shows F-measures when we used (a) a single sensor and (b) multiple sensors for each subject.



(a) Asphalt (b) Icy (c) Snowy (d) Foot-packed snow

Fig. 7. Pressure sensor values of subject A's left foot for each sidewalk surface condition. The horizontal and vertical axes are time and sensor value, respectively. Line colors represent different sensors.

TABLE I
SUBJECT ATTRIBUTES

Subject ID	Body weight [kg]	Shoe size [cm]	Has grown in snowing area?
A	68	26.0	✓
B	68	26.0	✓
C	56	27.0	
D	65	27.0	
E	53	26.0	✓
F	52	26.5	✓

When we choose the number of sensors from one to five, there are a total of 31 sensor combinations. When two or more sensors are used, there are multiple combinations. The results for two, three, and four sensors in Table II(b) are the mean F-measure of all the combinations of two, three, and four sensors, respectively. Table II indicates the following:

- We derived F-measures of more than 0.9 when we used two or more sensors. An F-measure was saturated for more than four sensors. An increased number of sensors resulted in the small improvement of the estimation performance. The number of sensors seemed to have a small impact on the surface estimation performance.
- Even with a single sensor, the mean F-measure was more than 0.9 except when we used a heel sensor. In Table II, cells with an F-measure lower than 0.9 are highlighted in gray. Except for the heel sensor, F-measures were more than 0.9 for more than half of the subjects. With a single sensor, the proposed method was almost successful in estimating the condition of the sidewalk surface.
- When using a single sensor, a hypothenar sensor showed the best mean F-measure of 0.934. We usually put a pressure on our feet for better grip on slippery surface apart from normal asphalt, which results in a big difference in hypothenar pressure. Figure 7 shows an example of foot pressure data of Subject A for each sidewalk surface condition. We can confirm the big difference in hypothenar sensor data derived on different surfaces.

The above results confirm that our proposed sidewalk surface estimation method successfully estimated surface conditions with the mean F-measure of more than 0.9.

D. *Performance with the Limited Training Data*

In the aforementioned experiment, a learning model was built on an individual basis using sufficient amount of training data. To evaluate the performance with a limited amount of training data in a practical situation, we evaluated an F-measure as a function of the size of the training data.

The amount of training data was controlled by the number of steps used in the feature extraction process. We extracted

TABLE II
F-MEASURE PER SUBJECT, PER SENSOR

(a) Single sensor

Sensor location	A	B	C	D	E	F	Mean	Median
Toe	.992	.959	.932	.880	.853	.908	.921	.920
Thenar	.963	.927	.957	.870	.940	.857	.919	.934
Root	.982	.952	.992	.915	.890	.873	.934	.934
Hypothenar	.997	.835	.977	.987	.997	.900	.949	.982
Heel	.982	.865	.879	.951	.820	.778	.879	.872

(b) Multiple sensors

# of sensors	A	B	C	D	E	F	Mean	Median
2	.993	.967	.975	.966	.969	.943	.969	.968
3	.996	.982	.979	.981	.985	.975	.983	.982
4	.997	.988	.984	.988	.995	.993	.991	.991
5	.997	.992	.992	.994	.993	.996	.994	.994

TABLE III
F-MEASURE FOR EACH SUBJECT AS A FUNCTION OF THE NUMBER OF STEPS

# of steps	A	B	C	D	E	F	Mean	Median
15	.997	.985	.988	.973	.956	.980	.980	.983
30	.997	.990	.989	.989	.967	.989	.987	.989
45	.998	.992	.992	.989	.981	.993	.991	.992
60	.998	.993	.995	.991	.993	.995	.994	.994

sensor data samples corresponding to specific number of steps and applied the feature extraction and classification processes described in Sects. III-C and III-D to estimate a surface condition. The number of steps was changed from 15 tp 60. We performed a random permutation cross-validation: we repeated the estimation process 10 times and calculated a macro F-measure for each number of steps.

Table III shows the macro F-measure for each subject as a function of the number of steps used for training. Table III shows the following:

- We derived the mean F-measures of more than 0.95 even when the number of steps used for training was 15. An F-measure was saturated for more than 45-step data. F-measures ware slightly improved by inceasing the number of steps from 15 to 30. An increased amount of data had a small impact on the estimation performance.
- Even with 15-step data, F-measures were more than 0.9 for more than half of the subjects. In Table III, cells with an F-measure lower than 0.98 are highlighted. Except for subjects D and E, F-measures were more than 0.98.

The above results confirm the proposed method successfully estimated surface conditions with the mean F-measure of more than 0.95 with a limited amount of training data.

V. Conclusion

In this paper, we presented the surface condition estimation method by collecting foot pressure data using newly developed insole devices. By incorporating step-related features, we estimate a sidewalk surface condition with a pre-trained machine learning model. The experimental evaluation showed that the proposed method estimated four types of surface condition with an F-measure of more than 0.9 for six subjects. We also confirmed that 15-step training data resulted in the estimation with an F-measure of more than 0.9.

In the future, we will increase the number of subjects and data to see if similar results can be obtained. We are also considering building the common learning model to further reduce the cost of building the learning model.

Acknowledgment

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