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The final publication is available at
http://www.tandfonline.com/doi/abs/10.1080/01691864.2014.996601?journalCode=tadr20

What kind of floor am I standing on?

Floor surface identification through full-body motions of a small humanoid robot

This study addresses a floor identification method for small humanoid robots that work in such daily environments as homes. The fundamental difficulty lays in a method to understand the physical properties of floors. To achieve floor identification with small humanoid robots, we used inertial sensors that can be easily installed on such robots and dynamically selected a full-body motion that physically senses floors to achieve accurate floor identification. We collected a training data set over ten different kinds of common floors in home environments. We achieved 85.7% precision with our proposed method. We also demonstrate that our robot could appropriately change its locomotion behaviours depending on the floor identification results.

Keywords: floor identification, small humanoid robot

1. Introduction

Sensing diversity achieves robust recognition functions for robots in various environments. Many types of sensors exist for robots, such as depth sensors, laser range finders, RGB cameras, and microphone arrays. One typical example that shows the importance of sensing diversity is Kinect, with which researchers can easily use depth information. Such inexpensive depth sensors dynamically increase the sensing ability of many robots. Combinations of existing and cheap depth sensors enable high-quality sensing systems. Therefore, we believe that increases in sensing diversity will contribute to advances in robotics research fields.

Sensing through physical interaction is one unique approach to increase the sensing diversity of robots. This approach is often used for small robots, such as pet and hobby types, because physical interaction with them is an essential mode of communication.

For example, researchers found that physical interaction with robots is useful in therapy and for enjoyment [1, 2]. Related to understanding such physical interactions between small robots and people, researchers developed sensing mechanisms to recognize human gestures [3, 4], full-body gestures [5], attitudes toward a robot [6], and a person's identification [7].

However, unlike understanding the physical interactions between small robots and people, few related works have addressed understanding environments for interaction with robots [8-10]. Since these works were only conducted with wheel-type robots, the kinds of physical interaction between robots and environments are such simple uses as a tactile probe or changes of forward/rotation speeds during locomotion. No research has focused on understanding the physical interaction between environments and such non-wheel-type robots as humanoid or multi-legged robots that can physically interact with various environments. We note that humanoid robots need to select appropriate walking motions depending on the floor surface; different from wheel-type robot, it is difficult to sense floor surfaces through locomotion before understanding floor surfaces for small humanoid robots, which did not have enough sensing capabilities. In other words, increasing of a sensing diversity such as floor surface identification would contribute to realize appropriate walking motion selections for such small humanoid robots.

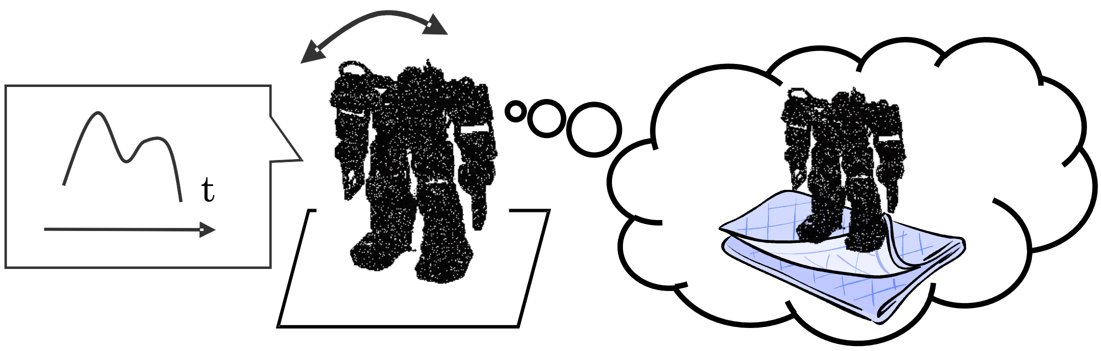

Fig. 1 Floor surface identification through physical interaction

The final publication is available at
http://www.tandfonline.com/doi/abs/10.1080/01691864.2014.996601?journalCode=tadr20

In this paper, to increase the sensing diversity of small robots, we propose a method that identifies an environment's property, i.e., its floor surface, by the full-body motions of a small humanoid robot (Figure 1). We though the number of unique points of this paper is three: 1) a use of a small humanoid robot to identify floor surfaces. Past research works which used humanoid robots to identify floor surfaces are limited to large humanoid robot with high sensing capabilities (details are described in next section). However, we tackled floor identification with only inertia sensors by focusing on physical interaction with the environments; this approach can be applied to other kinds of small humanoid robots.2) Physical interactions with environments through full-body motions. Different from large humanoid robots, small humanoid robots can easily interact with environment through full-body motions. Such interactions enable robots to gather features from sensors without locomotion motions; to begin with, humanoid robots could note use appropriate walking motions if a floor surface was unknown. 3) Iteratively narrowed down floor surface candidates using different kinds of full-body motions. This idea is inspired by human sensing actions by physical interactions; for example, a person can identify floor surfaces without visual information by different kinds of physical interactions, such as stamping or stroking.

The rest of our paper is structured as follows. Section II describes related work, and Section III introduces our proposed method that uses inertial sensors to identify floor surfaces through full-body motions. Section IV presents our experimental methods, and Section V presents the results. Section VI provides a discussion, and Section VII summarizes the contributions.

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2. Related work

Much research has measured environment properties using visual or distance information [11-13]. For example, Kuroki et al. proposed a method that identifies the surfaces where a robot can walk by stereo camera systems [14]. Okada et al. also developed a system that identifies flat floor spaces using a stereo camera system [15]. Hasegawa et al. used a small number of laser range finders with mirrors to find objects on a floor surface [16], and Yokoya et al. used multiple robots to efficiently construct 3D maps of an environment including its floors [17]. These research works enable robots to accurately measure floor properties.

From the viewpoint of increasing a small robot's sensing diversity, several researchers focused on physical interaction with environments to measure their properties. For example, DuPont et al. identified floor surfaces using the forward/rotation changes of a wheel-type robot [8]. Giguere installed a simple tactile probe on Roomba to identify various floor surfaces in a home environment [18]. They mainly focused on identifying floor surfaces because they are directly related to the locomotion planning of small robots.

However, different from our study, these research works which focused on physical interaction with environments to identify floor surfaces are limited to wheel-type robots. Such non-wheel-type robots as humanoid or multi-legged robots can execute more complex motions than wheel-type robots, and with those motions, gather various kinds of sensor data to accurately identify floor surfaces. For example, people can more accurately identify floor surfaces using such full-body motions as stamping their feet than driving over a floor by car or riding over it by bicycle. We propose a method to identify floor surfaces through such physical interactions as full-body motions with environments for non-wheel-type robots such as a humanoid robot; this concept is also a unique point of the paper, which focused on physical interactions between a small humanoid robot and environments.

3. Identification of interaction floor

3.1. Architecture

We propose a method to identify the floor surface on which a robot is standing by phasing the reductions of candidates, i.e., iteratively eliminating floor surfaces from a pool of candidates. Fig. 2 shows an overview of our implemented system with inertial sensory information. It selects an appropriate motion to gather the sensor data used to reduce the set of candidates (Section 3.2) and calculates the floor surface features by a time series of the inertial sensor data gathered by the selected motion (Section 3.3). These features identify floor surface candidates by a decision tree classifier that includes combinations of the current candidates and reduces the set of candidates (Section 3.4). The system finally identifies the floor surface on which the robot is standing by repeating these winnowing processes until only candidate remains.

Note that our proposed method assumes that only one floor surface exists while walking, and the data from the physical interaction were gathered beforehand.

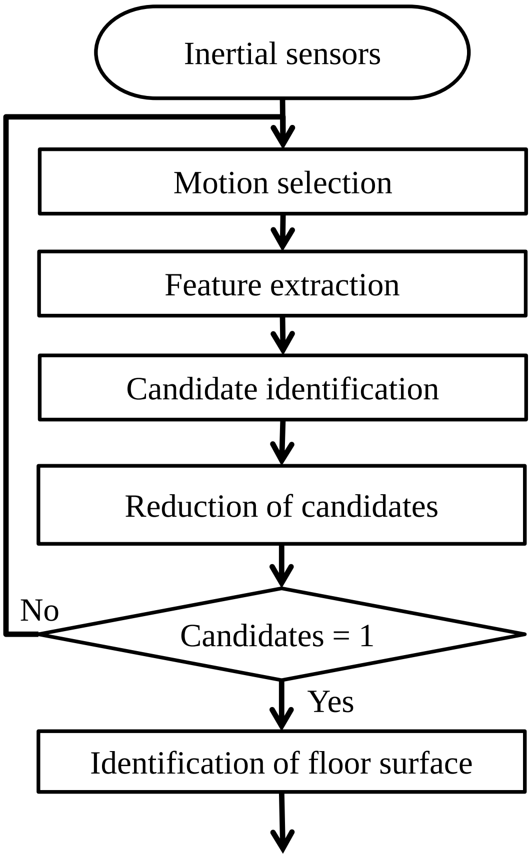


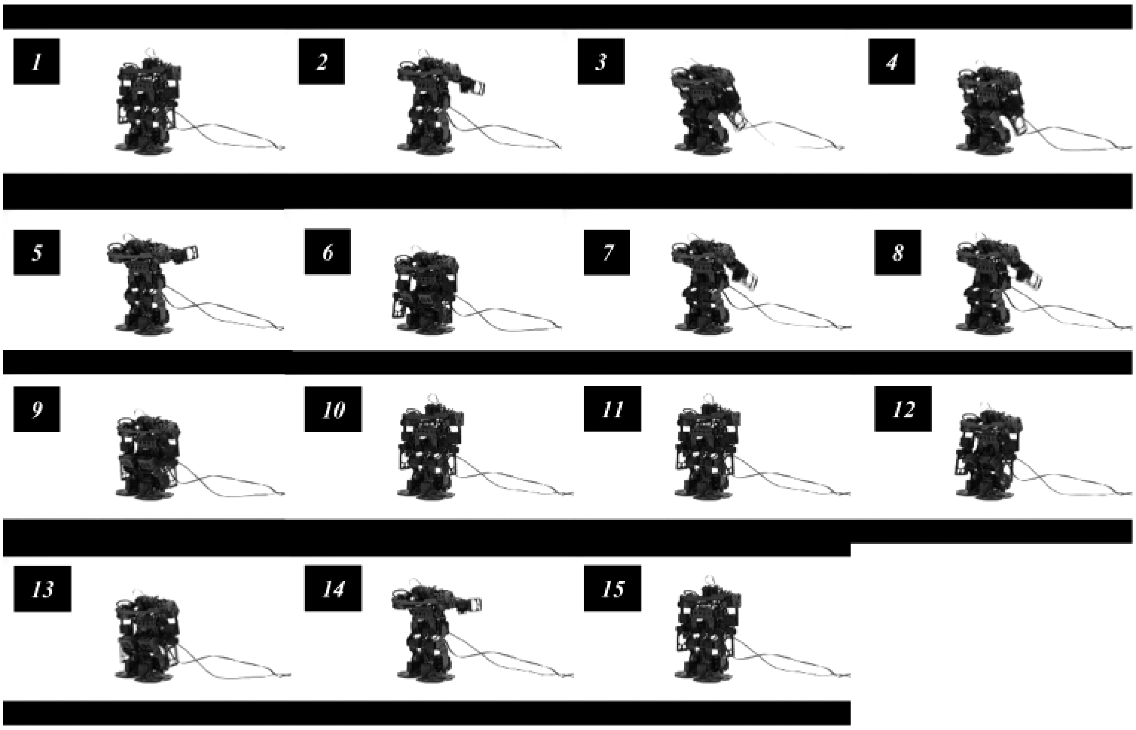
Fig. 2 Overview of proposed method

3.2. Motion selection

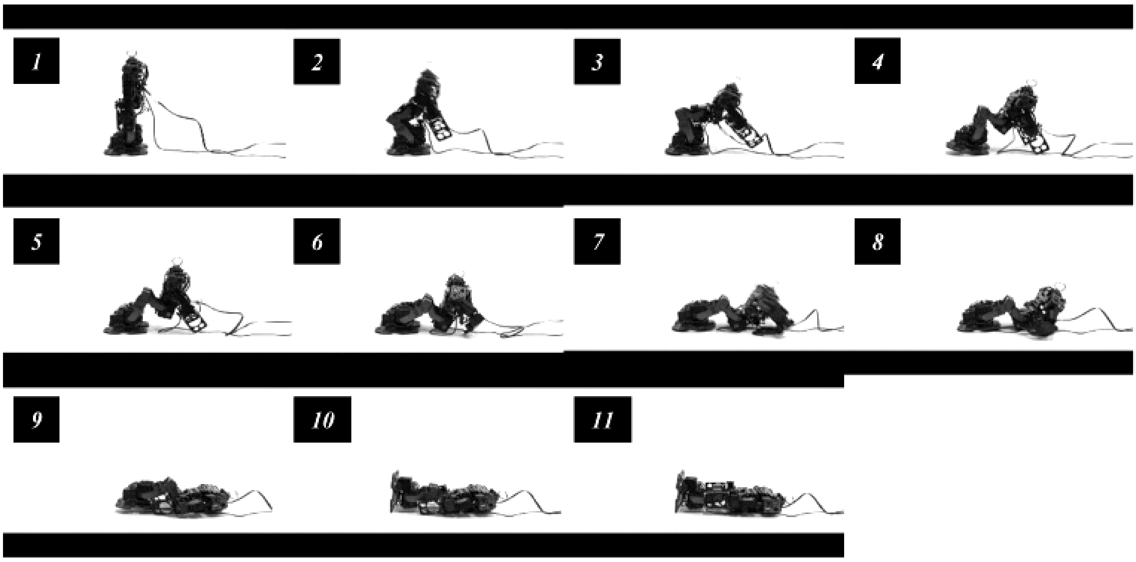
Our proposed method selects a motion to gather sensor data to identify floor surfaces from candidates. In this paper, we prepared four kinds of full-body motions that are designed to physically interact with an environment: bending and stretching, lying down, tossing and turning, and stamping (Figure 3).

The reasons of why we chosen these four motions are as follows. Basically we referred to behaviours of people, which are used to investigate floor properties without hands with preliminary testing with participants; we decided two motions, bending and stretching and stamping from observations of their behaviours. Moreover, we also focused on behaviours of people on beds. In such situations, we can estimate properties of beds and bedclothes via whole-body motions such as lying or tossing and turning. Different from large-sized robots, small-sized robot can easily conduct such behaviours; therefore we added these behaviours as full-body motions for the robot.

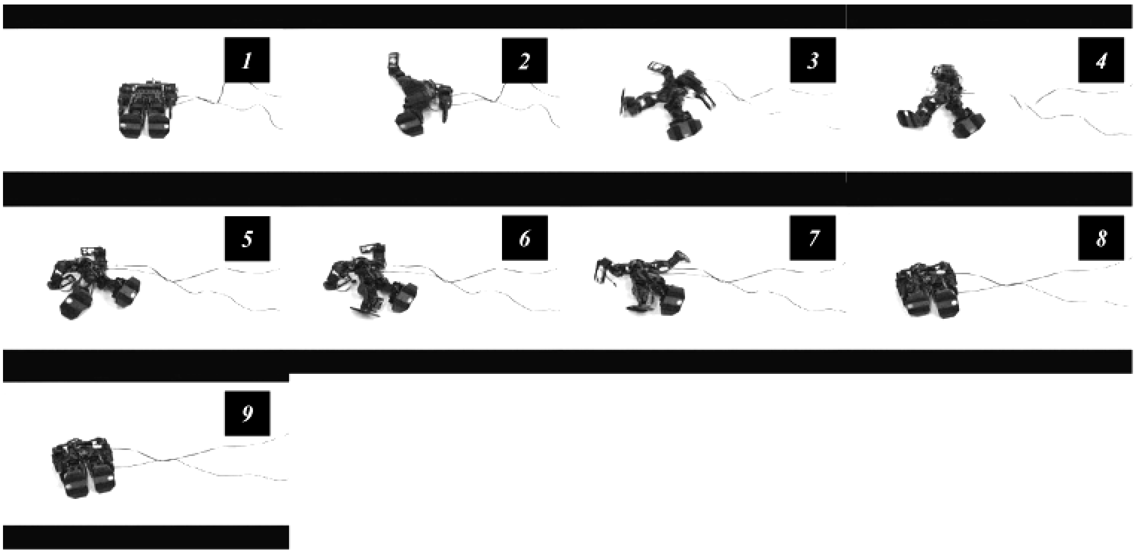
To identify the interacting floor surface, the system selects an appropriate full-body motion from above four motions (i.e., bending and stretching, lying down, tossing and turning, and stamping) to gather sensor data by considering the classifier reliability (the details will be described Section 3.4). At the first physical interaction with an environment, the candidates include all floor surfaces therefore a motion which has maximum classifier reliability towards the combinations of all floor surfaces is used to gather sensor data. After reducing the candidates, the system again selects an appropriate motion which has maximum classifier reliability towards the remaining candidates to gather suitable data to identify the interacting floor surface.



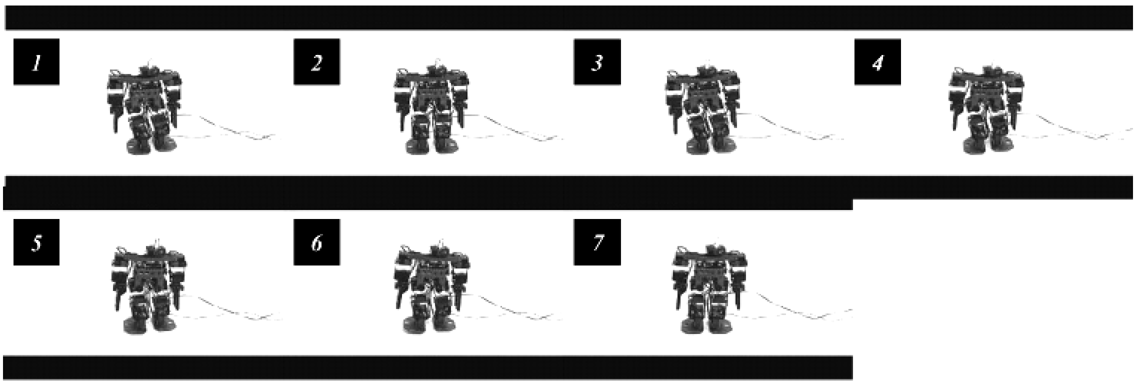
(a) bending and stretching



(b) lying down



(c) tossing and turning



(d) stamping

Fig. 3 full-body motions

3.3. Feature extraction

In this research, we calculated the first and second derivatives of the time series sensor data. We simply employed the two features of the sensor data of both time series, i.e., the mean and standard deviation to three kinds of sensor data: raw data, and the first and second derivatives of the time series of sensor data. They are defined as:

$$\mu = \frac{1}{n}\sum_{t_1}^{t_n} s(t) \qquad \textbf{(1),}$$

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{t_1}^{t_n}\left(s(t)-\mu\right)^2} \qquad \textbf{(2),}$$

where *s(t)* is the inertial sensor data (raw data, first derivative data, and second derivative data) at times *t*, and *n* are the amount of data in the time period. We used six kinds of features f (μ_r,μ_{d1}, μ_{d2}, σ_r, σ_{d1}, σ_{d2}) from each sensor to identify the floor surface.

3.4. Candidate identification and reduction of candidates

We applied a C4.5 decision tree classifier [19], which is widely used in robotics, to correctly identify the candidate that is interacting with the robot at each time step. This algorithm builds decision trees from training data set, based on the concept of information entropy. Based on the normalized information gain, the decision threes have node to split the classes from the training data. Each node automatically selects extracted features which are appropriate to split the classes, therefore this method is useful for a situation when it is still unknown, which features are appropriate for classification. In our method, mean and standard deviation of each sensor data are used as features to build decision trees.

We prepared multiple decision trees that considered all of the combinations among the candidates in advance of their phased reductions during the voting process. Each decision tree includes at least two classes, and thus the number of decision trees is calculated by this function:

$$NumOfTree = Mn + Mn\sum_{x=2}^{Nc-1} C(Nc, x) \qquad \textbf{(3),}$$

where *Mn* is the number of the full-body motion *Nc* is the number of classes, i.e., the number of candidates, and *C*(*Nc*, *x*) is the number of possible combinations of *x* from a set of *Nc*.

In our proposed method, the system stores the results from a decision tree using the extracted features to reduce the candidates. The candidate at each time step is calculated as

$$Candidate\ (t) = decision\ (RemainingCandidates,\ f\,(\mu_r, \mu_{d1}, \mu_{d2}, \sigma_r, \sigma_{d1}, \sigma_{d2})) \qquad \textbf{(4),}$$

where *decision* is a function that outputs a candidate using a decision tree classifier that includes the *RemainingCandidates*. In the first process, *RemainingCandidates* includes all candidates: *RemainingCandidates* = {A, B … *Nc*}.

Next, the system narrows down the floor surface candidates based on their reliability. The reliability of each candidate is calculated from a confusion matrix of the decision tree classifier. For example, the confusion matrix of the decision tree classifier shown in Table 1, reliability of “floor A” is 80% and “floor B” is 20 % when the decision tree classifier’s result was “floor A.”

Table 1 Confusion matrix example

A	B	
80	20	floor A
40	60	floor B

If a reliability is lower than a threshold, the candidate is removed in the next calculation process. The threshold value is defined as

$$Th = 1/(NumOfCandidates * \alpha) \quad \textbf{(5),}$$

where *NumOfCandidate* is the current number of candidates and α is a coefficient for the threshold calculation to increase the speed of convergence. The rest of the candidates are defined as

$$\begin{aligned} &RemainingCandidate = \\ &\{candidate \in CurrentCandidate \mid (Ratio(candidate) \geq Th)\} \end{aligned} \quad \textbf{(6),}$$

where *CurrentCandidate* is the set of the current candidates.

If *RemainingCandidate* includes more than two candidates, the system repeats the above processes by selecting a motion to gather sensor data until only one candidate remains. To select a motion for the next calculation, the system considers the values of the average recognition ratio toward *RemainingCandidate* and its standard deviation calculated by each classifier. For example, in a case of table 1, average recognition ratio is 70% and standard deviation is 14.14. The system selects the motions with the largest average recognition ratio towards *RemainingCandidate for* identification (if the number of selected classifiers exceeds 2, it uses the minimal standard deviation from them). We note that at the first interaction between the robot and the environments, the system selects a full-body motion with the largest average recognition ratio of all the floor surface candidates.

We describe an example case where the system identifies a ceramic tile from ten candidates. Firstly the robot selected "stamping" motion to gather sensor data towards the combinations of all floor surfaces because it has maximum classifier reliability for ten candidates. The robot extracted features from sensor data through the stamping motion. Through these processes, *RemainingCandidate* is reduced to two kinds: ceramic tile and tatami. The robot again selected the stamping motion to gather sensor data towards the combinations of ceramic tile and tatami because this motion also has maximum classifier reliability for the candidates. Finally, the robot identifies the floor surfaces as "ceramic tile."

4. Experiment methods

To investigate our proposed method's performance, we collected data when a small humanoid robot physically interacts with various floor surfaces.

4.1. Robot hardware

For the data collection, we used a small human-like robot called Robovie-MA (Fig. 4) that has two arms (4 DOFs for each), a body, a waist (2 DOF), and two legs (6 DOF for each). To record the inertial sensor data during the interaction, we attached two 2-axis acceleration sensors (ADXL202E, ANALOG DEVICES Inc.) to its body (Fig. 4). The sensor arrangements are designed to record 3-axes (X, Y, and Z) using two inertial sensors with 60-Hz sampling rates (Fig. 4). Therefore, the system calculated 18 features from the physical interactions between the robot and the environments. We adopted the simple moving average method as a kind of low-pass filter to reduce the noise of the sensor data. In this work, we used three steps data to calculate the average values.

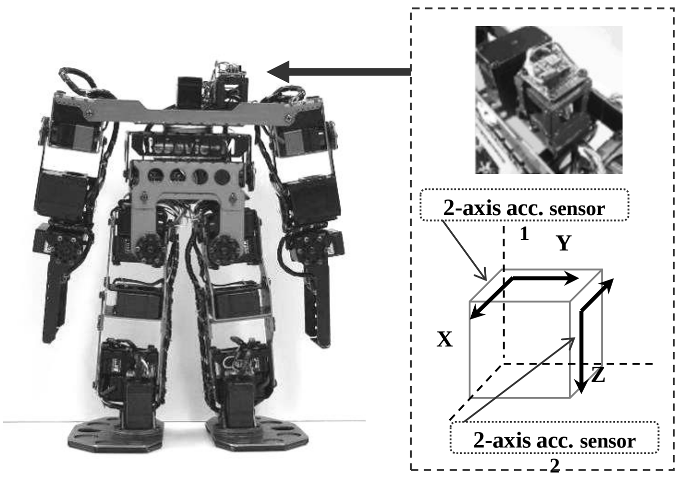
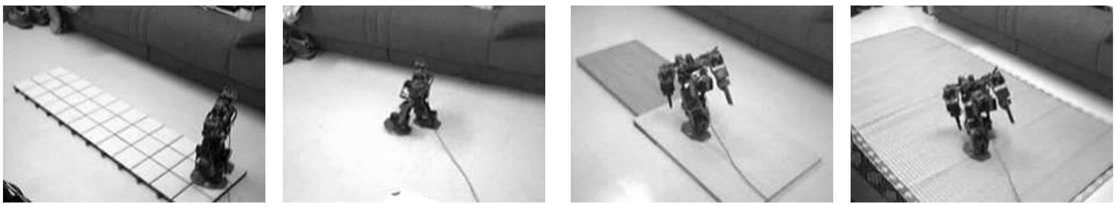


Fig. 4 Robovie-MA

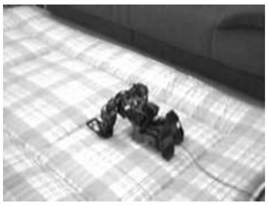
4.2. Data collection procedures

For the data collection, we used ten kinds of floor surfaces found in home environments: ceramic tiles, linoleum, wood, tatami mats (a type of mat used as a flooring material in traditional Japanese-style rooms), cushions, bedding, carpets, bath mats, blankets, and artificial turf. We installed these floor surfaces to a flat place as shown in figure 5.

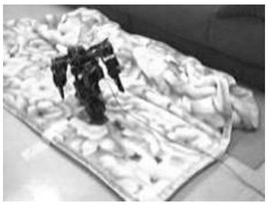
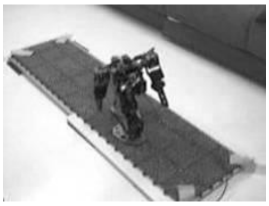
The robot executed for four kinds of full body motions on each floor (described in Section 3.2) to gather the inertial sensor data 60 times. Finally, we gathered a data set comprised of 2400 sensor data (60 times x 10 floors x 4 motions). Figure 6 and 7 shows acceleration data when the robot used the full-body motions on the bathmat and the robot used the stamping motion on the different surfaces; as shown in the figures, properties of sensor data are different due to the floor surfaces; for example, frequencies and maximum values of XYZ data are different between the floor surfaces. These differences are essential to identify floor surfaces in our method; therefore proposed method selects an appropriate full-body motion to gather sensor data to identify interacting floor surfaces.



(a) ceramic tile (b) linoleum (c) wood (d) tatami mat

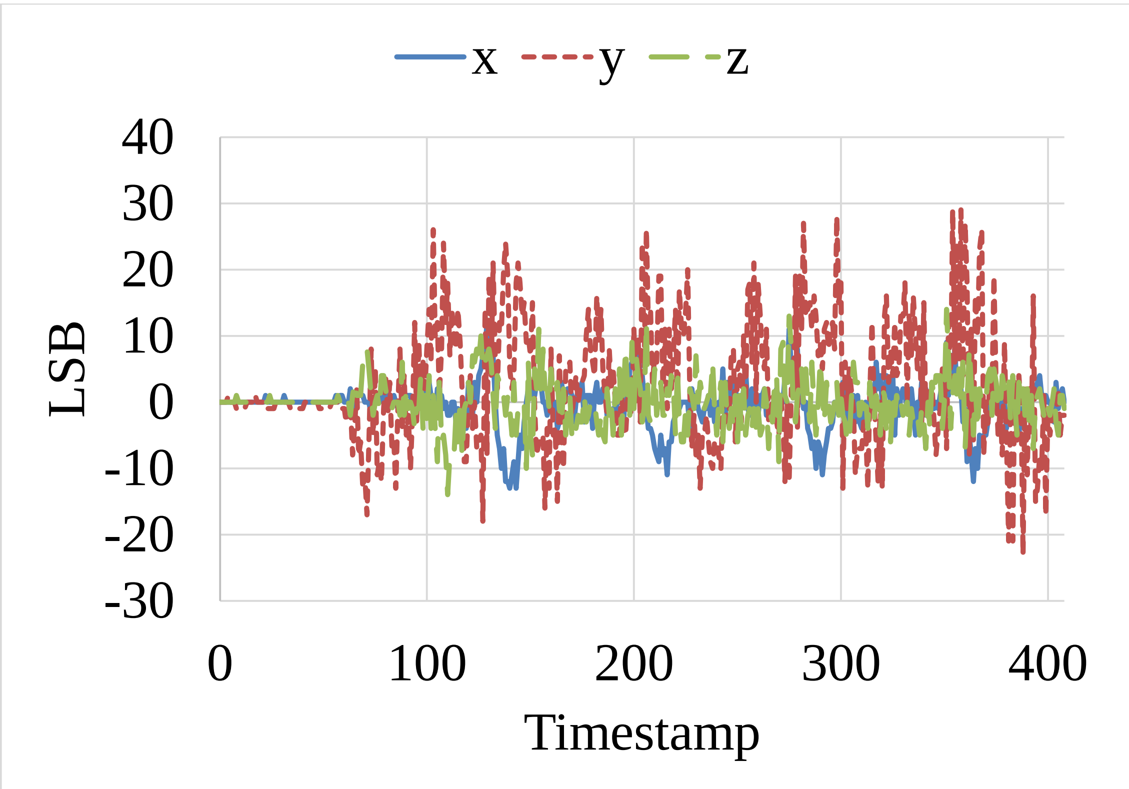



(e) cushions (f) bedding (g) carpet (h) bath mat

(i) blanket (j) artificial turf

Fig. 5 Floor surfaces for data collection



(a) bending and stretching

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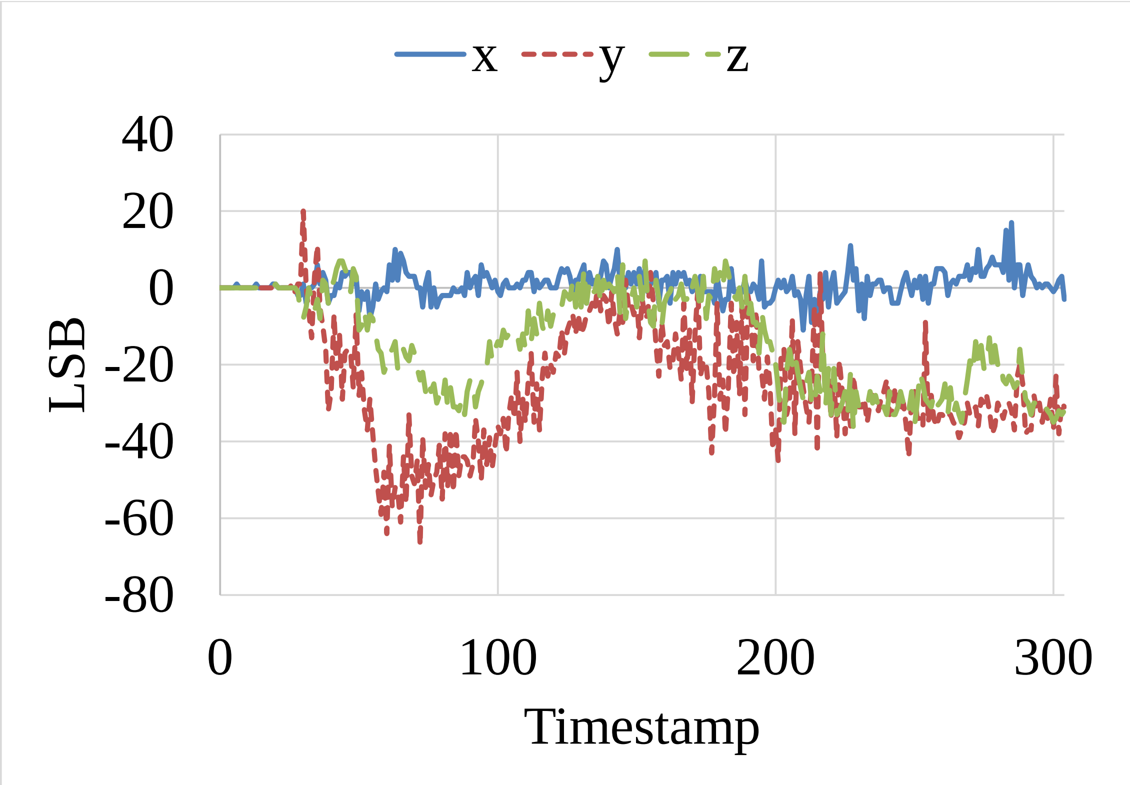
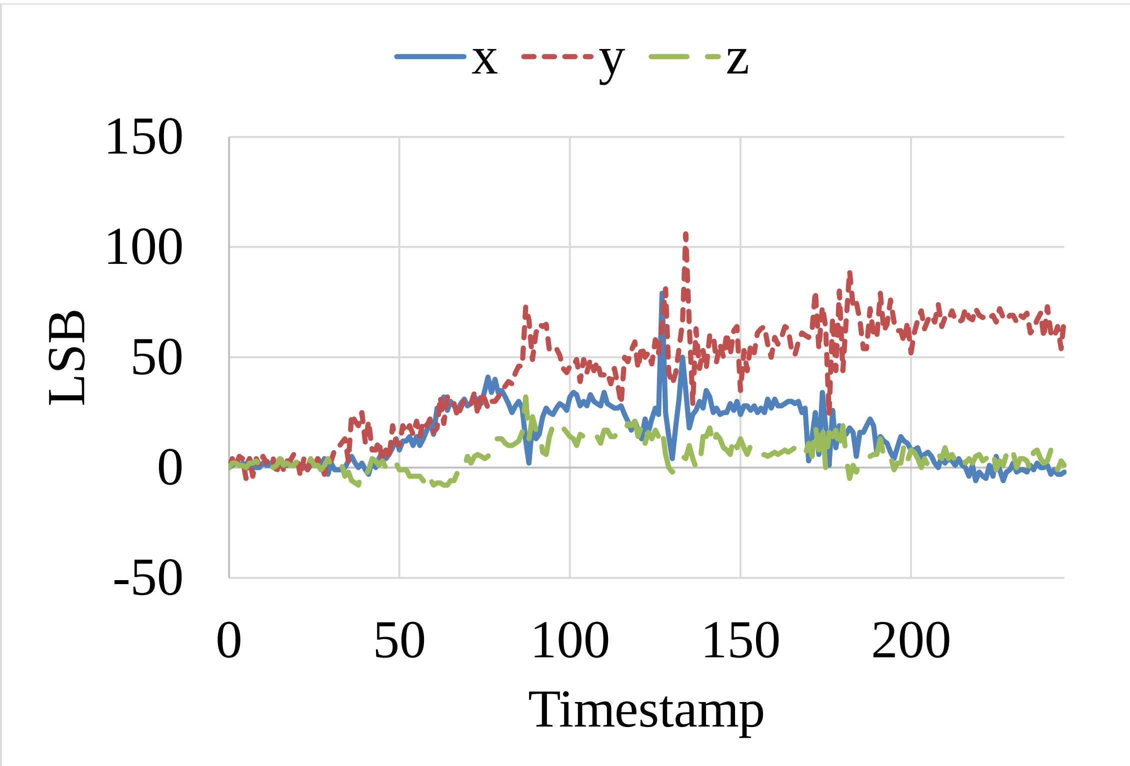
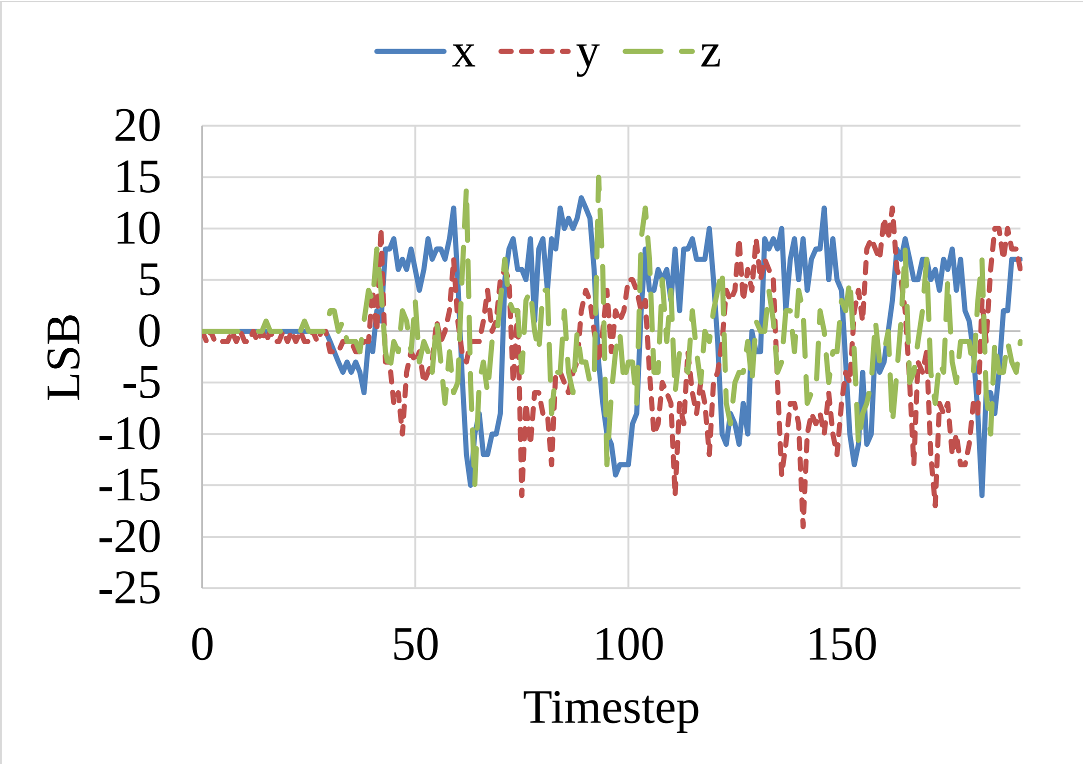


(b) lying down

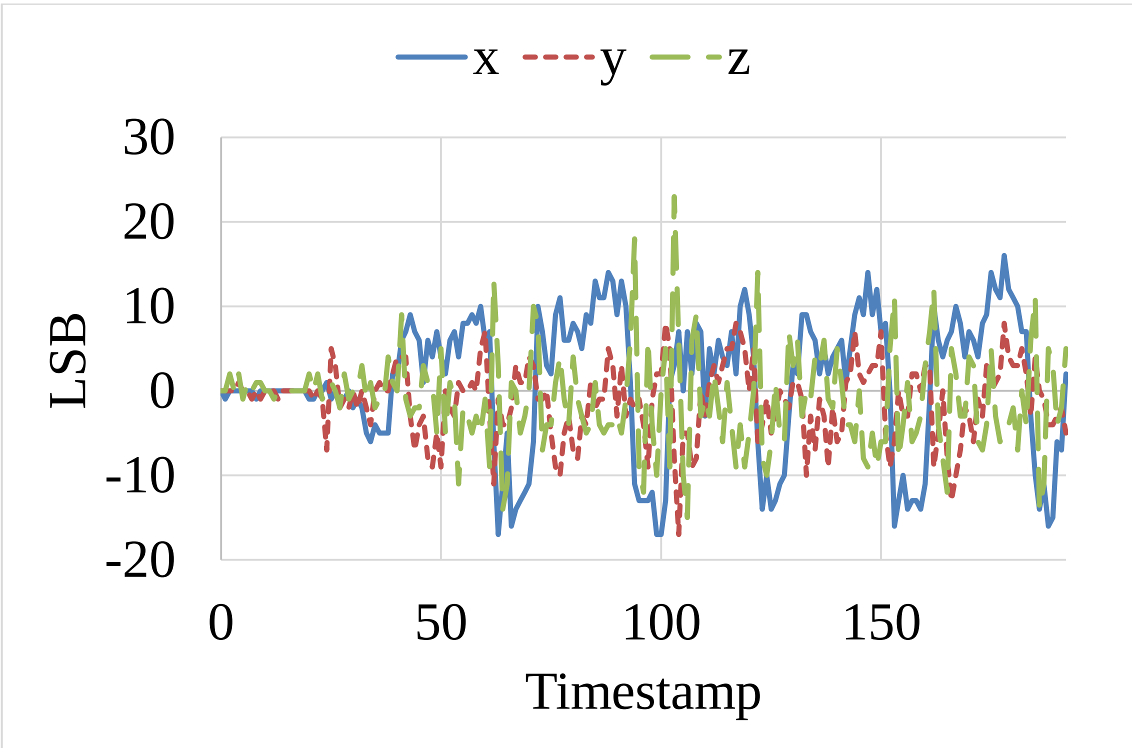


(c) tossing and turning

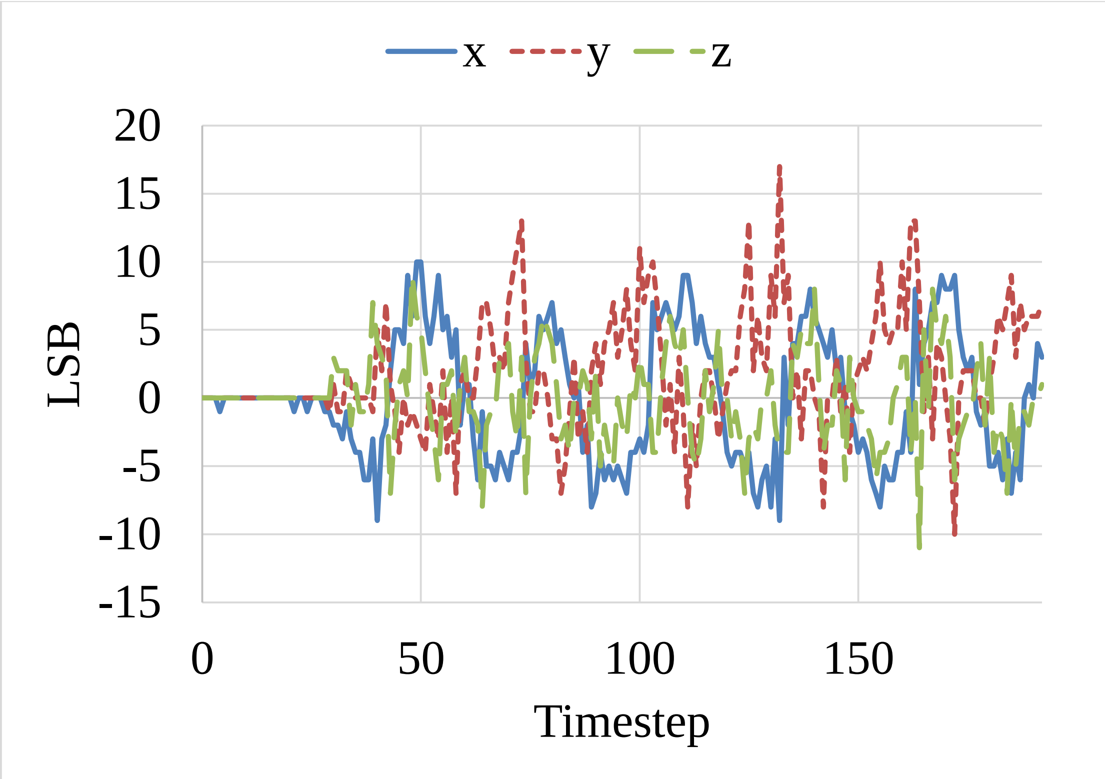


(d) stamping

Fig. 6 Sensor data with stamping motion at different floor surfaces. The unit of Y axis is LSB value of acceleration sensor, the range is 128 (+2G) to -127(-2G).



(a) ceramic tile



(b) futon

Fig. 7 Sensor data with stamping motion at different floor surfaces. The unit of Y axis is LSB value of acceleration sensor, the range is 128 (+2G) to -127 (-2G).

4.3. Experimental design and data analysis

In the experiment, we measure performance of our floor surface identification though off-line process. For this purpose, we conducted a 5-fold cross-validation for gathered data. We used a 1920 data set (48 times x 10 floors x 4 motions) to construct decision tree classifiers (these processes can be done before the experiment but not in real time) and a 480 data set (12 times x 10 floors x 4 motions) to test the identification in each validation.

At the first step, the system selects an appropriate full-body motion to gather inertial sensor data toward the candidate which includes all floor surfaces.

Inertial sensor data was replayed by the collected data, and the system reduces the candidate floor surfaces based on the sensor data. Then, the system again selects an appropriate full-body motion to gather inertial sensor data towards the remaining candidates until identifying the candidate. The maximum number of calculation cycles is 12; if the system failed to reduce the number of floor surface candidates to one during the 12 calculations, it selects the floor surface with the maximum ratio from the candidates as an identification result. We determined the coefficient of α in Eq. (6) to be 2.5. These parameters are based on heuristic tuning with the test data.

In this experiment, we prepared four alternative methods to investigate the effectiveness of our proposed method. These methods only used one full-body motion to gather the sensor data, unlike the proposed method that selected full-body motions to gather sensor data that depend on the floor surface candidates. We compared the alternative methods to reveal the effectiveness of selecting full-body motions to identify floor surfaces.

5. Results

5.1 Performance evaluation

Table 2 shows the performance of each method (Precision, Recall and F-measure) and Figure 8 shows the results of the floor surface identification. Table 3 shows a confusion matrix with the proposed method, which achieved 85.7% floor surface identification through physical interactions; the alternative methods achieved 80.7%, 65.8%, 46.5%, and 73.8% precisions. In the proposed method, wrong identification mainly occurred for relatively hard floors such as ceramic tile, linoleum and tatami mat. On the other hand, there are good performances for soft floors such as cushions and blanket.

Table 2 Average success ratio of methods

	Precision	Recall	F-measure
Proposed method	85.7	87.4	86.0
Bending and stretching only (a)	80.7	82.2	80.5
Lying down only (b)	65.8	67.0	65.8
Tossing and turning only (c)	46.5	47.6	45.8
Stamping only (d)	73.8	82.1	73.5

Table 3 Confusion matrix of the proposed method

a	b	c	d	e	f	g	h	i	j	
44	1	13	0	0	2	0	0	0	0	a = ceramic tile
4	43	13	0	0	0	0	0	0	0	b = linoleum
0	11	47	0	0	0	2	0	0	0	c = wood
1	0	3	55	0	1	0	0	0	0	d = carpet
0	0	0	0	60	0	0	0	0	0	e = cushions
11	0	9	0	0	40	0	0	0	0	f = tatami mat
0	2	1	2	0	0	55	0	0	0	g = bath mat
0	0	0	0	2	0	0	58	0	0	h = bedding
0	0	0	0	0	0	0	0	60	0	i = blanket
0	0	0	0	3	0	3	0	2	52	j = artificial turf

Fig. 8 Identification rate of each floor

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5.2 Frequency of use of motions

Table 4 shows the ratio of the full-body motions in our proposed method. The ratios of bending and stretching and stamping are relatively higher than the other full-body motions, but all of them were selected as appropriate motions for floor surface identification during the calculations. For example, "Tossing and turning" showed higher reliabilities towards specific combinations of candidates, such as "Cushion" and "Blanket" than other full-body motions. In other words, this motion was appropriate to identify the floor surfaces from the combinations of soft floor surfaces. These results showed that mixing of various motions contribute to increase the performance of the proposed method in total.

Table 4 Ratio of full-body motions

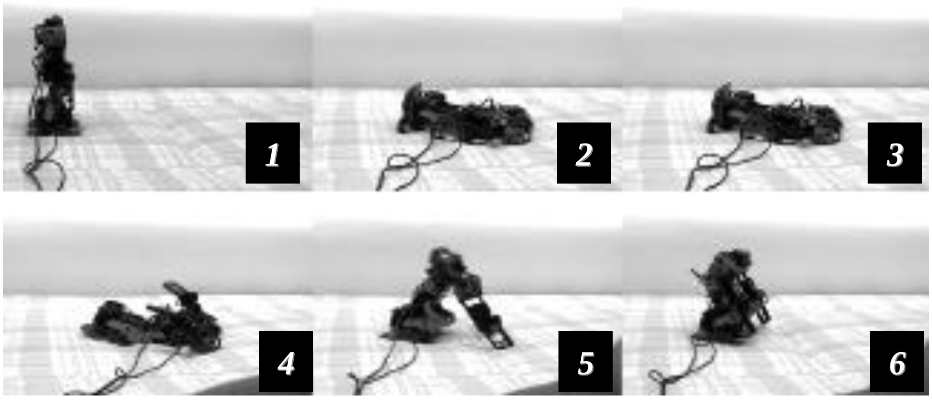
	Usage rate
Bending and stretching	32.9
Lying down	19.0
Tossing and turning	9.2
Stamping	38.9

6. Discussion

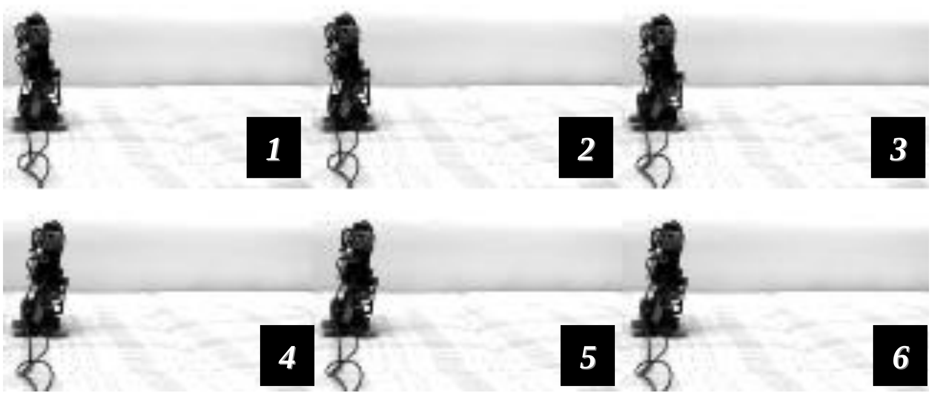
6.1 Applications

The identification of floor surfaces can be used to change/modify a robot’s motion. In particular, the locomotion planning of such non-wheel-type robots as a humanoid robot is strongly affected by the floor surfaces. Our proposed method will help such robots move in home environments that include various floor surfaces.

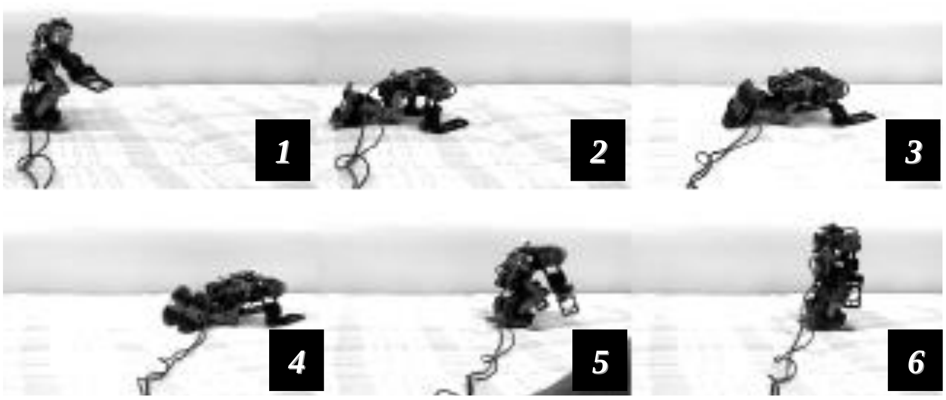
Next we show an example application of our proposed method for a function that enables a small humanoid robot to use suitable movements depending on the floor surfaces. Fig 9(a) shows a robot walking on bedding. Since its motion is not stable, it falls down. After that, the robot used a stamping motion to gather sensor data to identify the floor surface (Fig. 9(b)); after correctly identifying the floor surface, it used a crawling motion to move on it; the robot walked over the bedding (Fig.9(c)).



(a) robot falling down on bedding



(b) robot uses stamping motion to gather sensor data



(c) robot uses crawling motion to move on this floor surface

Fig. 9 Examples of locomotion behaviors on bedding

Such applications can be realized by referring to past research that identified floor surfaces. However, as noted in the introduction, the unique point of our proposed method is increasing the sensing diversity for small robots. Unlike typical methods, it does not need any visual or distance information to identify floor surfaces. For example, our proposed method can identify floor surfaces under complete darkness or those that easily change their form due to the robot's weight, such as cushions.

Combinations of our proposed method and past research will increase the sensing capability of small robots. Our proposed method enables greater robust sensing systems by collaborating with previous work.

6.2 Scalability for number of candidates

We evaluated our proposed method with data from ten floor surfaces using four full-body motions. If the number of floor surfaces increases, our proposed method should be able to identify them, although it might require more interaction with the floor surfaces using more full-body motions. With more targets, since similar floor surfaces will also increase, more interaction with the floor surfaces is needed for identification.

6.3 Scalability for number of candidates

In total we gathered each 60 sensor data set for each floor (10 floors) with each full-body motion (4 motions). To confirm the validity of the number of trials, we investigated differences between the data set. Figure 10 shows the plot data by using the first/second principal components. Circles represent data set gathered by each full-body motion (a= bending and stretching, b=lying down, c= tossing and turning, d= stamping). We note that contribution rate of them is 0.55, and the ratio of between-class variance and within-class variance was 5.70. Figure 11 showed a part of floor data sets: futon and wood (a) and artificial turf and linoleum (b). As shown in the figures, the data sets gathered by each full-body motion at each floor are crowded; the differences of data sets within each floor are smaller than the differences of them between each floor. Therefore, we thought that the gathered data in the experiment would be enough to evaluate the performance of the proposed method, by considering the variances of gathered data sets.

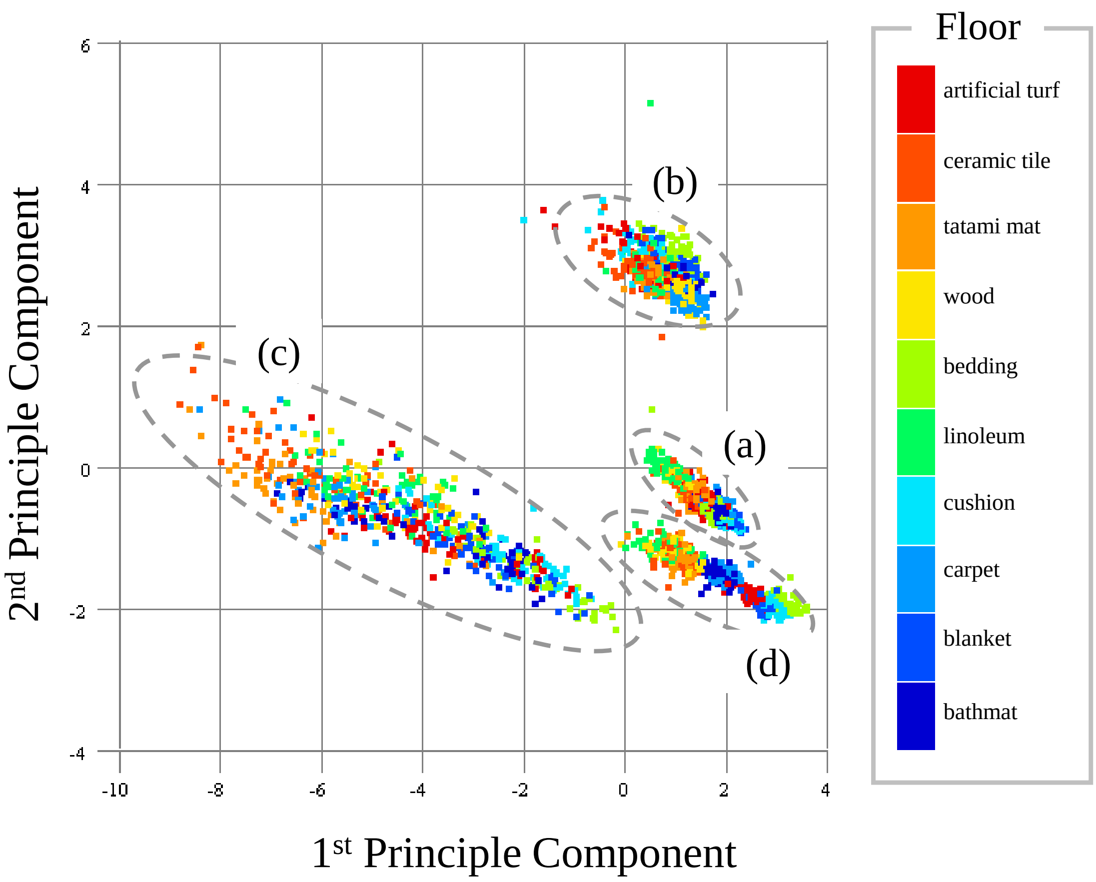
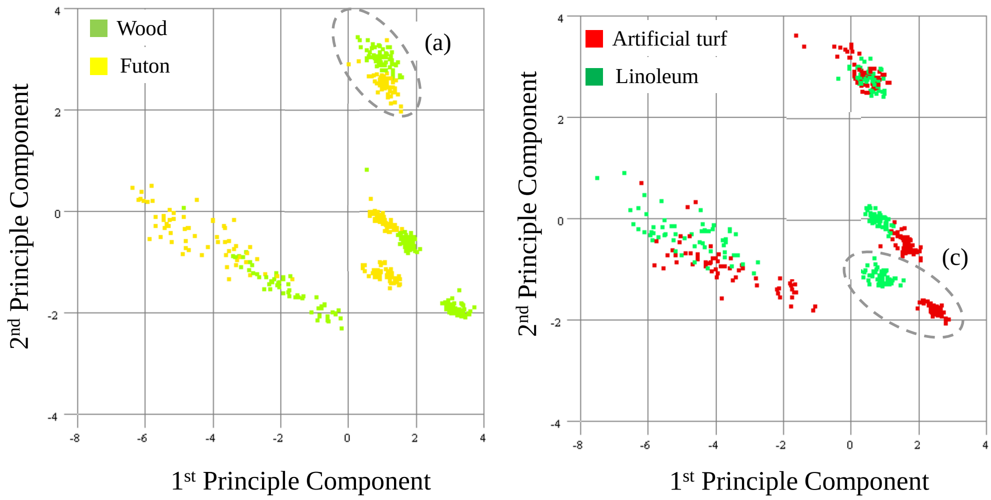


Figure 10 Plotted data with principle components

The final publication is available at
http://www.tandfonline.com/doi/abs/10.1080/01691864.2014.996601?journalCode=tadr20



(a) Wood and futon (b) Artificial turf and linoleum

Figure 11 Plotted data of specific floor combinations

6.4 Limitations

Our proposed method identified floor surfaces through physical interactions with 85.7% accuracy, but we did not compare its performances with other state-of-the-art time series classification algorithms, such as Support Vector Machine [20], an existing method that uses inertia sensors to identify environments [18], and an approach that discriminates different textures using whisker sensors [21-23].

Our method can only identify one floor surface because it assumes that a small robot interacts with just a single floor surface at a time. Moreover, winnowing candidates requires observation of a full-body motion within a certain time to find the differences between floor surfaces. We also evaluated our proposed method with one small humanoid robot with a specific sensor arrangement. If our proposed method is used with different kinds of robots, the parameters must be calibrated and the sensor positions adjusted.

Surface identification was conducted using an existing data set. Therefore, a registration process is needed beforehand, such as gathering physical interaction data with floor surfaces. Such processes are also needed for other types of floor surface identifications, such as vision-based systems, but our proposed method needs more time for registration than these vision-based methods.

In this research work, we used a specific humanoid robot and inertial sensors. It would be difficult to share the same decision trees between different kinds of robots; we thought that our method can be applied to other kinds of humanoid robots with different sensors by rebuilding decision trees by using them. We note that one concern of our method is for a humanoid robot which is covered by soft materials. If the robot whole-body is covered by sponge or silicon skins, inertial sensor data might become more similar between different kinds of floor surfaces.

7. Conclusion

We proposed a method that identifies floor surfaces through the physical interaction of a small robot. Our work's unique concept is to increase the sensing diversity for non-wheel-type small robots such as a humanoid robot; it focuses on the differences in the extracted features from the inertial sensor data during physical interaction to identify the floor surface on which the robot is standing. Our proposed method extracts the features from the inertial sensor data history and narrows down the floor surface candidates through physical interaction. We evaluated its performance, and our evaluation results showed that it identified floor surfaces through physical interactions with 85.7% precision. We believe these results demonstrated the concept that physical interaction with an environment is effective to increase the sensing diversity for robots by dealing with floor surface identification problem. Accurate floor surface identification would contribute motion planning for robots, in particular small humanoid robots, which work on daily environments where various floor surfaces exist.

Acknowledgements: This research was supported by the Strategic Information and Communications R&D Promotion Programme (SCOPE), Ministry of Internal Affairs and Communications (132107010).

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