Pedestrian Dead Reckoning Based on Human Activity Sensing Knowledge

Yuya Murata
Graduate School of Engineering, Nagoya University
1 Furo-cho, Chikusa-ku,
Nagoya, Aichi, 464-8603 Japan
murata@ucl.nuee.nagoya-u.ac.jp

Kei Hiroi
Institute of Innovation for Future Society, Nagoya University
1 Furo-cho, Chikusa-ku,
Nagoya, Aichi, 464-8603 Japan
k.hiroi@ucl.nuee.nagoya-u.ac.jp

Katsuhiko Kaji
Graduate School of Engineering, Nagoya University
1 Furo-cho, Chikusa-ku,
Nagoya, Aichi, 464-8603 Japan
kaji@nuee.nagoya-u.ac.jp

Nobuo Kawaguchi
Institute of Innovation for Future Society, Nagoya University
1 Furo-cho, Chikusa-ku,
Nagoya, Aichi, 464-8603 Japan
kawaguti@nagoya-u.jp

Abstract

This research addresses improvement of the accuracy of pedestrian dead reckoning (PDR), which is one effective technique to estimate indoor positions using smartphone sensors. Even though various techniques using step lengths and their number have been previously proposed for PDR, insufficient accuracy is gotten from smartphone sensors. In this research, we define human activity sensing knowledge and propose improvements to PDR accuracy based on it. Human activity sensing knowledge consists of four kinds of information: pedestrian, environmental, activity, and terminal. Previous studies separately used these kinds of information; however, no study has systematically arranged them for use in PDR. We improved PDR accuracy by adjusting the step length in passages and on stairs and revised activity recognition error with human activity sensing knowledge. To investigate the effectiveness of that strategy, we used HASC-IPSC, which is an indoor pedestrian sensing corpus. After our investigation, activity recognition accuracy improved from 71.2% to 91.4%, and the distance estimation error was reduced from approximately 27 m to approximately 7 m using human activity sensing knowledge.

Author Keywords

pedestrian dead reckoning; activity recognition; smartphone; sensor

ACM Classification Keywords

H.1.2 [User/Machine Systems]: Human information processing.

General Terms

Documentation, Standardization

Introduction

Pedestrian dead reckoning (PDR) with acceleration and gyro sensors is one effective technique to estimate the indoor positions of people. PDR uses steps, step lengths, and walking directions to estimate current positions by the displacement from the immediately previous position. Even though various techniques have been proposed for it, their performances using smartphone sensors remain inadequate.

In this research, we define human activity sensing knowledge and propose improvements to PDR accuracy based on it. Human activity sensing knowledge consists of four kinds of information: pedestrian, environmental, activity, and terminal. Previous studies used such information separately [9][7]; no study has systematically integrated it for PDR. We improved PDR accuracy by adjusting the step lengths in passages and on stairs and revising the activity recognition error with human activity sensing knowledge.

Related Work on PDR

Traditional PDR generally estimates the number of steps, their length, and the walking direction from acceleration, gyro, and geomagnetism data [3]. However, this technique accumulates errors because it estimates the current position by displacement from the immediately previous one.

To revise the accumulative error of PDR, techniques using RFID tags and map matching have been proposed. Anzai [2] reduced errors by map matching in corners. Positions are revised when the system determines by geomagnetism and gyro sensors that a pedestrian turned or changed her walking direction.

Korogi [12] proposed an RFID positioning system with map matching to revise pedestrian positions. When an RFID reader detects a tag with a specific ID, it notifies the user of the positional information and the detection time by a network to revise the position. In addition, movement through floors indoors is limited to stairs and elevators or escalators. Therefore, with a map, we can revise the pedestrian position when the system detects an elevator or escalator.

Previous studies realized position estimation with high precision using RFID tags and map matching in PDR. But these techniques need maintenance, management, and elaborate prior investigation infrastructure and design. If PDR precision is high, this cost can be cut by reducing the amount of infrastructure or the labor of preliminary surveys. Highly precise position estimation with lower cost is necessary to improve PDR accuracy.

Definition of Human Activity Sensing Knowledge

Such factors as psychological conditions, the clothing being worn, and weather conditions influence pedestrians and their walk environments [13]. Among these factors, pedestrian, environmental, and activity information are easy to use at low cost and are useful to improve PDR accuracy. In addition, terminal information using pedestrian observations is also easy to use at lower cost to improve PDR accuracy because the sensor precision is different. Therefore, in this research, we arrange this information as pedestrian, environmental, activity, and terminal information and define them as human activity sensing knowledge.

We also improve PDR accuracy by adjusting the steps in passages and on stairs to correct the activity recognition error by human activity sensing knowledge.

We obtain such information by two methods: the information input by users and the information estimated by the system. The information input by users is easy to get without maps or documents; the information estimated by the system is obtained by machine learning from sensor data.

Pedestrian Information
We define the physical information and the health condition of walkers as pedestrian information. The number of steps and their lengths are affected by many factors about the walkers, including age, gender, and psychological conditions [13]. For setting the step lengths in PDR, the walker's height is often used. Even though gender and age also influence the step length [13], we don't consider them. Usually, there is no difference of step length between genders. However, when walking speed exceeds 130 m/min, the step length is influenced by gender. The step length is also changed by the walker's age. The ratio of the step length by height changes by age. Walking patterns begin to change for people in their 50s, and step length and pace become shorter in their late 60s. The step length is 45% of the walker's height when people are younger than 65 years, although when they are over 67, it decreases to 40% of the walker's height [13]. As the walking speed increases, the influence of age becomes bigger. Gender and age information are not used very much in PDR, although both are useful for precise improvement. The existence of obstacles and gait differences also affect step length and their number. But using them is difficult because they vary greatly among people.

Therefore, we concentrate on such physical information as gender and age and the walker's health condition.

Environmental Information
We define the outline of the environment and its buildings as environmental information. Walking is influenced by the corridor situation and the blockage percentage [13]. Step lengths on stairs or on slopes are different from the steps in passages. If we have a floor map or detailed building information, we can reduce the error by map matching. Map matching is available at low cost if we use a floor map as an image [11]. Such information as the congestion degree is also easy to use and is probably useful for PDR precision improvement. Since easily available information about pedestrians does not take time to update, it is available at low cost. In this study, environmental information includes data that are assumed to be identical in the same building, such as the ceiling height and the width of a single step on stairs. But it doesn't include data that vary according to places such as the distance of passages.

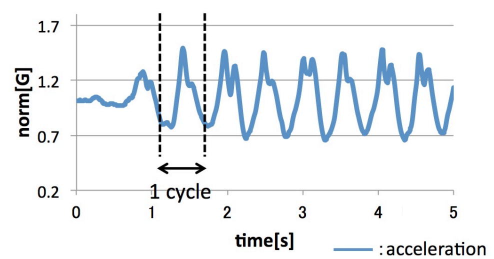
Activity Information
We define a kind of action of pedestrians and their characteristics as activity information. In this definition, we only focus on activities when they can walk normally. Pedestrians perform various actions, including stopping, walking, and going up or down stairs. All actions have

characteristics. We can determine which movements the walker does based on such characteristics. The frequencies of the differences among walking, running, and going up and down stairs are observed. A technique was proposed that used a power spectrum and a peak appearing in a frequency band [7]. EE The difference between going up stairs and walking is observed in the patterns of the gyro sensor data. The difference between going down stairs and walking is observed in the differences of the peak value of the vertical acceleration and the acceleration of the running direction [11]. Some studies used an atmospheric pressure sensor to detect going up and down stairs as well as the number of floors [4]. But few smartphones are equipped with atmospheric pressure sensors. Precision is crucial for the information provided by this identification. If the identification is correct, we can improve PDR precision using activity information. But if the identification is not correct, the PDR precision worsens. When a walker moves, we suppose that she navigates directly without encountering any obstacles. In addition, since we assume that she takes the same action if the walking environment doesnft change, we can use such information to improve PDR precision.

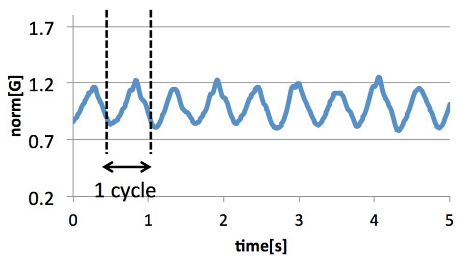
Terminal Information

We define the kind and the maintenance position of the sensor terminals as terminal information. Such sensor terminals as smartphones or private terminals are used in PDR. They are equipped with the sensors of different manufacturers, so we assumed that their sensor precision is different. Iokura pointed out that the sampling intervals of acceleration sensors are different in each version of an Android OS, even if the models are identical [6]. Haba identified a delay in the acquisition of wireless LAN electric wave information that is different in all available models [5]. Since such sensor terminals affect PDR precision, they must be considered for PDR. In addition, the sensor data greatly differ from every position of a sensor terminal whose position is important to PDR. Some studies estimate the sensor terminal's position [10]. The figures show the sensor data from the following positions: hand-held (Fig. 1(a)), a pants' pocket (Fig. 1(b)), and rear middle of the waist (Fig. 1(c)). A low-pass filter is applied to these data.

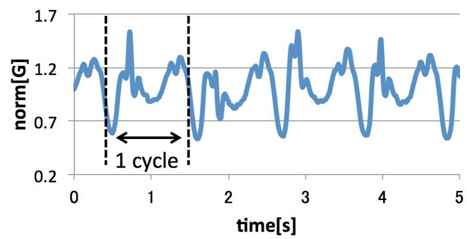
In the case of the hand-held and the rear middle of the waist positions, a rhythm is seen every wavelength. When carried in a pocket, the rhythm is seen every two wavelengths because the foot movement affects the sensor data. In step detection, the norm of acceleration sensor data is used in many cases. Therefore, we must use an appropriate detection method for the terminal's maintenance site. Various studies estimate sensor terminal positions with sensor data [10]. If the estimation is correct, it is available for precision improvement in PDR. However, wrong estimation increases error.



(a) Hand-held



(b) Pocket



(c) Waist: rear

Figure 1: Sensor data of each position

Evaluation

To confirm the accuracy improvement, we performed distance estimation and activity recognition with the human activity sensing knowledge. We investigated the effectiveness of our proposed technique using HASC-IPSC [8], which is an indoor sensing corpus. HASC-IPSC contains the data of 107 men and women whose ages range from their 20s to their 60s. The data include route data in buildings and such basic activities such as staying and walking.

Experiment content

We performed activity recognition and distance estimation with route data from HASC-IPSC. The activity recognition was performed with the route data of 107 walkers. We performed the distance estimation with the data of five walkers from the same route. In this experiment, we got correct information about the position of the terminal and the corners. In the activity recognition and distance estimation, we used the HASC Tool [1].

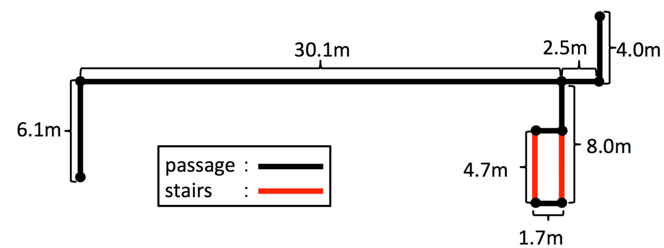


Figure 2: Route (2D)

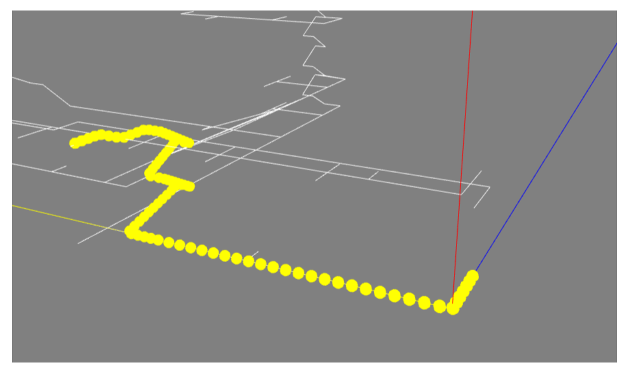


Figure 3: Route (3D)

Human activity sensing knowledge
In this experiment, we used the following human action sensing knowledge.

Pedestrian information
: We adjusted the step length by the walker's height and age. We assumed that the step length is 45% of the walker's height of people who are younger than 65. When they are over 65, we assumed that their step length is 40% of their height.

Environmental information
: There are 12 steps on the stairs in this building. We assume that one step length is 0.3 m, and one step height is 0.15 m. The stairs have a landing, and the size of the landing is approximately 2 m In addition, the walker always turns before entering the stairs, which are perpendicularly placed in the entrance.

Activity information
: The actions from a corner to the next corner are the same because the stairs and the passages are divided by a corner in this experiment's route. The walkers moved linearly from a corner to the next corner.

Terminal information
: We used Nexus 4 (OS: Android 4.2) made by LG Electronics Incorporated and put it at the rear middle of the waist of the walkers. We used one wavelength for the step detection.

The table shows the pedestrian information used in our experiment.

Table 1: Pedestrian information

	Height [cm]	Age	Gender
Person 1207	178	20	Male
Person 1208	171	20	Male
Person 1217	168	30	Male
Person 1234	174	50	Male
Person 1296	147	60	Female

Activity Recognition
We performed activity recognition by the route data of all the walkers. Since few terminals have atmospheric pressure sensors, we only used acceleration and angular velocity sensors. The kind of action was estimated by machine learning using the characteristics. For them, we used the maximum, the minimum, the mean, and the variance of the three axial gyro sensor data and the norm of the acceleration sensor data. We used a J48 decision tree of Weka in machine learning and the human action sensing knowledge for the activity recognition. For the activity information, we assumed that the walker takes the same action from one corner to the next one. We calculated the total time for each action from one corner to the next and decided the longest time action as the section's action. Based on the environmental information, there is a landing on the building's stairs. We regarded the short section between the stairs as a landing. We improved the precision of our activity recognition using human activity sensing knowledge. For the learning data, we used the basic action data of all the walkers included in HASC-IPSC and show the activity recognition result in Table 2.

Table 2: Activity recognition rate (%)

	Walk	Up stairs	Down stairs
Walk	88.8 (55.0)	4.6 (22.3)	6.6 (22.7)
Up stairs	1.6 (7.6)	93.5 (81.2)	4.9 (11.2)
Down stairs	7.4 (15.2)	0.7 (5.5)	91.9 (79.3)

The number in the parentheses expresses the activity identification rate when we did not use the human activity sensing knowledge. With the activity and environmental information in the human activity sensing knowledge, we improved the activity recognition rate. Without the human activity sensing knowledge, some results identified walking as going up stairs. Between the stairs, there is a landing that is shorter than the stairs. Therefore, they probably affected the recognition result.

Distance Estimation
Using the activity recognition results, we performed distance estimation. When the walker travels along the route, she does her usual walk and goes up and down one step of the stairs. We show the route in Figs. 2 and 3. The black line shows the passages, and the red line shows the stairs. The route's full length is 74.9 m with four stairs. This route goes from the first to the third floors.

We calculated the distance by multiplying the steps by their length. We adjusted the step length using the pedestrian and environmental information. When the estimated activity is walking, we adjusted the step length using the pedestrian information. When the estimated activity is going up or down stairs, we adjusted the step length using the environmental information.

For step detection, we applied a threshold to the norm of acceleration sensor data. We show the detection state in Fig. 4.

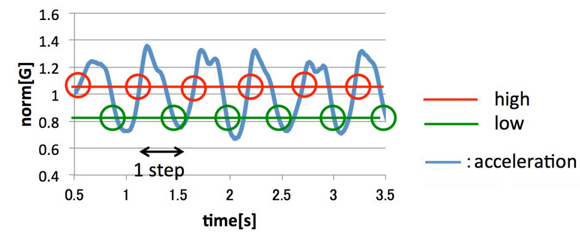


Figure 4: Step detection

We set high and low thresholds. When the norm of the acceleration sensor data is under the low threshold within about one second after the norm of the acceleration sensor data exceeds the high threshold, we count it as one step. In this experiment, we set the high threshold to 1.1 G and the low threshold to 0.95 G. 1G shows the size of gravity's acceleration.

Table 3: Distance estimation in stairs

	Mean error [m]		Improvement rate [%]
	Without knowledge	With knowledge	
Person 1207	6.1	0.8	86
Person 1208	6.2	0.9	86
Person 1217	4.9	0.8	84
Person 1234	4.0	1.5	63
Person 1296	4.4	0.5	87

We show the result of walking on stairs in Table 3 of the distance estimation with the environmental information. The number shows the mean error in four times of walking up the stairs. We show the error for the route's full length in Table 4. This expresses the error of the horizontal movement distance.

By the environmental information in the human activity sensing knowledge, we can reduce the error for all the walkers. The error on the stairs also greatly influenced the distance estimation. Using this distance estimation technique, we converted a walker's position during the route into coordinates. We show the mean error in Table 5 when we compared it with the correct position every 0.1 seconds. The correct position was derived from the correct data included in HASC-IPSC.

Although we used the human activity sensing knowledge, some errors have not been improved yet. Some estimation accuracy worsened because the route's stairs are half-turn stairs. The half-turn stairs refuted the error reduction in the stairs using the knowledge. The figure shows the error with the correct position every 0.1 seconds when a walker moves in the route.

Table 4: Error for complete route length

	error [m]		Improvement rate [%]
	Without knowledge	With knowledge	
Person 1207	28.4	4.3	85
Person 1208	42.0	19.5	54
Person 1217	22.6	0.7	97
Person 1234	16.7	5.6	66
Person 1296	23.0	4.6	80

Table 5: Position estimation precision

	Mean error [m]		Improvement rate [%]
	Without knowledge	With knowledge	
Person 1207	3.9	3.8	3
Person 1208	4.9	5.5	-12
Person 1217	6.5	6.2	5
Person 1234	2.8	2.9	-4
Person 1296	2.3	3.8	-65

The colored part in the graph is the stairs. Although we adjusted the step length, errors increased in the stairs because the cumulative error negatively influenced the accuracy. In addition, the result of the activity recognition of Person 1296 was partly wrong. The step length varies based on places. Differences in recognition increased the error.

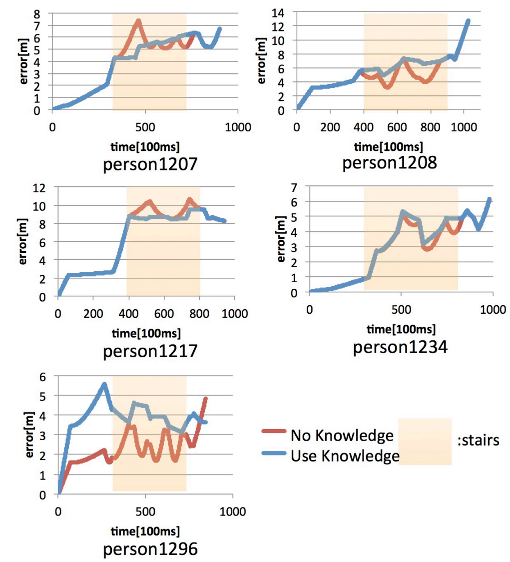


Figure 5: Errors during route

Conclusion

Summary

We defined human activity sensing knowledge to improve PDR accuracy and proposed obtaining activity recognition and distance estimation based on it. Human activity sensing knowledge consists of four kinds of information:

pedestrian, environmental, activity, and terminal. We evaluated it using route data from HASC-IPSC, tested it, and confirmed the effectiveness of our proposed technique for activity recognition and distance estimation. With human activity sensing knowledge, the accuracy of activity recognition improved from 71.2% to 91.4%, and the distance estimation error fell from approximately 27 m to approximately 7 m. Although we used human activity sensing knowledge, some errors failed to improve because the route had multistage half-turn stairs. In addition, cumulative error influenced it and worsened the precision. Therefore, improvement of the position estimation precision when walking through corridors is necessary.

Future work includes the following.

- Improvement of human action sensing knowledge
  We defined human activity sensing knowledge in this study and explained how to use it. However, because it is thought that there are more applications which are useful for precise PDR improvement, further examination is necessary about the usage of human activity sensing knowledge.

- Adjustment of step length
  Height and age are used for setting the step length. A step length estimated by that information is the same as the normal step length. However, since step length is changed by walking speed and environment, we must adjust it based on them.

- Improvement of positioning accuracy based on corner estimation
  In our evaluations, we used correct information at the maintenance position of a corner and a terminal. However, we must estimate them for real environments.

Acknowledgement
Part of this research was supported by the Strategic Information and Communication RD Promotion Program (SCOPE).

References
[1] HASC Tool. http://hasc.jp/tools/hasctool-en.html.
[2] Anzai, K., Okajima, S., and Tsubokura, H. The estimate of the indoor position that used a smartphone and the suggestion of the walk navigation system [in japanese]. In *Multimedia, Distributed, Cooperative, and Mobile Symposium*, vol. Vol. 2011 (2011), pp. 921–927.
[3] Beauregard, S., and Haas, H. Pedestrian dead reckoning: A basis for personal positioning. In *Proceedings of the 3rd Workshop on Positioning, Navigation and Communication* (2006), pp. 27–35.
[4] Collin, J., Mezentsev, O., Lachapelle, G., et al. Indoor positioning system using accelerometry and high accuracy heading sensors. In *Proc. of ION GPS/GNSS 2003 Conference* (2003), pp. 9–12.
[5] Haba, T., Kaji, K., and Kawaguchi, N. Influence of Wireless LAN Reception Delay in Positioning Method Integrating Multiple Sensors [in Japanese]. *(Proceedings of the 76th National Convention of IPSJ* (2014).
[6] Ioroi, S., Suzuki, T., and Tanaka, H. Multiple floor dead reckoning using a smartphone built-in sensors [in japanese]. In *Multimedia, Distributed, Cooperative, and Mobile Symposium*, vol. Vol. 2013 (2013), pp. 723–735.
[7] Itoh, M., and Ma, J. Indoor location estimations using sensor data and situation detection [in

japanese]. *The Special Interest Group Technical Reports of IPSJ Vol. 2011*, No. 11 (2011), pp. 1–8.

[8] Kaji, K., Watanabe, H., Ban, R., Kawaguchi, N. HASC-IPSC: Indoor Pedestrian Sensing Corpus with a Balance of Gender and Age for Indoor Positioning and Floor-plan Generation Researches. *International Workshop on Human Activity Sensing Corpus and Its Application (HASCA2013)* (2013).

[9] Kamisaka, D., Muramatsu, S., Iwamoto, T., and Yokoyama, H. Dead reckoning method by hand for pedestrian navigation system [in japanese]. *IPSJ Journal Vol. 52* (2011), pp. 558–570.

[10] Kouchi, S., and Fujinami, K. A recognition system for stored positions of a pedestrian ' s smart phone including stationary states [in japanese]. *Proceedings of the 75th National Convention of IPSJ Vol. 2013*, No. 1 (2013), pp. 149–151.

[11] Kourogi, M., and Kurata, T. Personal positioning based on walking locomotion analysis with self-contained sensors and wearable camera [in japanese]. *Technical report of IEICE. PRMU Vol. 103*, No. 737 (2004), pp. 25–30.

[12] Kourogi, M., Okuda, T., and Kurata, T. Indoor positioning system using a self-contained sensor module for pedestrian navigation and its evaluation [in japanese]. *Proceedings of symposium on mobile interactions Vol. 2008* (2008), pp. 151–156.

[13] Yamasaki, M., and Sato, H. Human walking: With reference to step length, cadence, speed and energy expenditure [in japanese]. *Journal of Anthropological Society of Nippon Vol. 98*, No. 4 (1990), pp. 385–401.