Daily Action Dead Reckoning Using Smartphone Sensors

Takumi Otsuki[1], Kohei Kanagu[2], Kota Tsubouchi[3], and Nobuhiko Nishio[4]

[1] Ritsumeikan University, Shiga, Japan
tsukky@ubi.cs.ritsumei.ac.jp
[2] Yahoo Japan Corporation, Tokyo, Japan
kingu@ubi.cs.ritsumei.ac.jp
[3] Yahoo Japan Corporation, Tokyo, Japan
ktsubouc@yahoo-corp.jp
[4] Ritsumeikan University, Shiga, Japan
nishio@cs.ritsumei.ac.jp

Abstract. Pedestrian dead reckoning (PDR) is easy to introduce because it requires no equipment for the environment. PDR results can provide an atomic physical behavior such as step detection and turning in walking, however providing a flexible response to a user's daily actions other than walking like sitting, moving in a line or standing is tough. Our research objective is to make PDR more usable in spite of these daily actions by estimating the movement situation using the same sensor information as conventional PDR. We applied a state transition in the movement situation recognition using the transition restrictions existing between the moving situations. A new method for moving context recognition using machine learning with accelerometer and gyroscope feature vectors simultaneous with PDR is proposed herein. The experiments show that, the movement situation recognition and the state transition technique are efficient for the whole dead reckoning performance. The proposed method can also be applied to improve the PDR positioning accuracy.

1 Introduction

Positioning techniques have been actively studied in the recent years with the spread of services using location information. Indoor location information is useful because it can be used for working management of factory workers and navigation in a complex urban indoor environment, among others. Pedestrian dead reckoning (PDR) is a typical positioning method that is functional in both indoor and outdoor environments and achieved by continuously estimating the walking conditions, distance and direction using the accelerometers, gyroscope and magnetometer of the user's smartphone, and assimilating these measurements to estimate the current position. Moreover it does not depend on the environment thereafter and does not require extra equipment.However, the problem is that positioning errors are accumulated. Since PDR is a relative positioning method, no absolute location calibration arrives. Therefore, our research focuses on the user's most of all kinds of movement not only walking steps that may cause any positioning error. The current PDR, only focuses on walking recognition the other body action states of the user are hardly considered. An erroneous step detection when sitting in a chair at the same place, which is a daily action often seen indoors is confirmed because of the changing leg or body posture and one's orientation even though he/she does not move at all. For example, we frequently perform a changing movement in posture and body orientation, stay at the same place with some steps , or sit for a long time as well as perform irregular walking in which stopping is frequently and forcibly repeated such as in the line or during congestion (hereinafter referred to as non-moving state). These states include motion without movement, which leads to a false detection of walking and direction estimation in PDR. The sitting condition requires to distinguish it from the standing condition which may start moving at any time. The machine learning technique is effective in recognizing such irregular actions and states. In order to improve the positioning accuracy, some methods perform movement or state identification using highly expensive and high-precision sensors such as the Inertial Measurement Unit(IMU)[3]; however, such devices are not available for smartphones. The other methods using extra sensors and fixing them at specific positions for all would bring many limitations. Aside from clarifying the user's moving state, this study also performs PDR positioning by simultaneously performing state/motion recognition using the learned model and PDR positioning and algorithm optimization according to the estimated result of the model. We propose a new positioning method called daily action dead reckoning to minimize the accumulated errors and improve the positioning accuracy.

2 Related work

2.1 Activity recognition using a smartphone

Makita et al.[3] determined 11 types of walking motions and states including a context that does not follow the movement that is difficult to predict based on only tracked walking trajectory(e.g.sitting motions) using a sensor device attached to the waist.Their recognition achived with 90% accuracy or more. However, it is burdensome for the user to wear the sensor on a part of the body. As a method without a sensor device attached to the body, Pei et al.[4] used a smartphone in a pocket to recognize bending considering the walking speed, walking state, running state, and stop. Whether Cosukun et al.[5] proposed a method that recognizes the walking(e.g. climbing stairs) and running conditions. KHAN et al.[6] combined 15 smartphone acceleration sensors, microphones and barometric pressure sensors to identify 15 daily activities and conditions. All of the previous studies identified the way of walking, etc., which was different from the user's movement state recognition that is the purpose of the present research.

2.2 PDR using another sensor

One method uses the IMU as a method of utilizing other sensors. The IMU is a very high accuracy sensor compared to the micro electro mechanical system mounted on a general smartphone and often used for PDR. Coskun et al.[5] used an IMU attached to the foot to estimate the leg angle etc. and optimize the PDR according to the angle to reduce the positioning error of the PDR. Park et al.[2] classified the user's movement and condition into eight using an IMU attached to the leg and used it for PDR positioning. However, the IMU is a very expensive sensor, and it has many limitations such as the need to fix the holding state to a part of the body.

2.3 PDR using the walking context recognition results

Qian et al.[7] estimated the attitude of the smartphone held by a user and identified the holding state of the smartphone such as calling using the smartphone, holding it putting it in the pocket and typing characters. Depending on the identification result, they then optimized the PDR algorithm and improved the positioning accuracy. However,this method cannot dynamically change the algorithm and works only with a single algorithm. Tian et al.[8]also estimated the attitude of the smartphone held by a user including holding the smartphone, swinging, and putting it in the pocket. They subsequently optimized the PDR algorithm according to the identification result. Kanagu et al.[9]classified the state of searching for products generated during shopping from the appearance of walking into three states, and aimed to improve the positioning accuracy. Their method was limited because the target environment was super.

3 Daily action dead reckoning(DDR)

Fig. 1 shows the system flow of the proposed method which was divided into the learning and evaluation phases.

3.1 Learning phase

In the proposed method, we created a model by logistic regression. Logistic regression is a regression model classified as supervised machine learning having the features that enable finding useful features because the weight of each feature that leads to classification is known. Normal walking is defined as ”walking”, walking which is similar to stopping is defined as ”moored walk”(e.g, crowded). Standing is defined as ”stop”, sitting is defined as ”sitting”. In addition, we also identify standing and sitting movements for using the state transitions(3.1)

Evaluation phase In the evaluation phase, the user's walking context is determined by analyzing the sensor data using a trained context-aware model. The adopted t value is the same as that used in the learning phase. The extracted

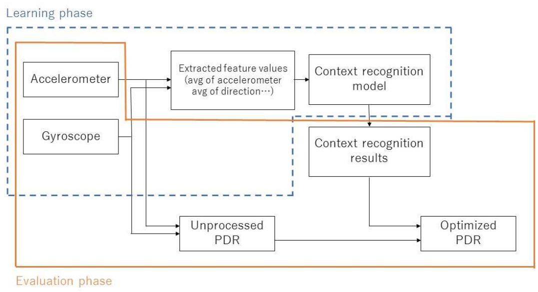

Fig. 1. Processing flow of the proposed method

feature vectors are plotted on the data space, and a trained context recognition model detects the context of the feature vectors. The identified walking context is merged with the ordinal PDR result to obtain the PDR result with context information. The PDR algorithm is adapted to the PDR method proposed by Yoshimi et al. [1] who accumulated changes in the stride and direction estimated by the sensor data to identify the user's indoor location at that time.

State transition Fig .2depicts the behavior and state identified by the proposed method and considered to be transitioning between some behaviors and states. The sitting state is next to the sitting motion. The sitting motion is after the sitting state. Some transitions cannot occur. For example, when the walking state occurs after the sitting motion or the sitting state occurs after the leaving motion, either of the discrimination results is erroneous. Therefore, if a class cannot be transitioned, the state transition is performed to avoid making a transition. The figure shows a state transition diagram that omits impossible transitions. In the proposed method, the decrease in the discrimination accuracy between the sitting and stop states can be by provided by identifying the action that triggers the sitting state such as the sitting and standing actions. However, problems also occur in this case. In the proposed method, the sensor value is cut out in time series (the length of the cut-out time is taken as the window width) to calculate the feature amount, but the window is appropriate in the state(e.g. sitting action and walking state) and the width is different. It is necessary to return the window width for short continuous operation and long continuous condition. If the length is short, sufficient features for walking can not be acquired, and if the length is long, the motion may be buried. In the proposed method, state transition is done by creating two classifiers with different window widths and integrating the classification results.

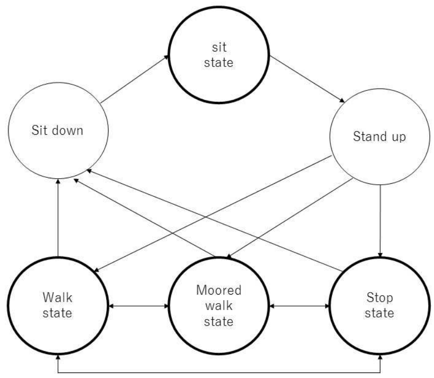

Fig. 2. State transition

Optimization of the PDR algorithm A state of moving straight ahead toward a destination is assumed for walking. This was the method used by Yoshimi et al[1]which was adopted as a normal walking algorithm. In moored walk, in a crowd or in a line, walking and stopping are continuous, and a stride may become short;therefore a filtering algorithm that ignores a certain amount of change in the movement direction is omitted. The stop assumes that the vehicle stops and does not move;thus it does not use Yoshimi et al's gait detection algorithm and does not change the user's current location. Similarly, step detection is turned off while sitting down. However while sitting down, the direction of the body does not significantly change from the time when it first sat;therefore it maintained the direction when facing the same direction for a fixed time or more. When away from the seat reset to the direction it was holding.

4 Evaluation

4.1 Experiment condition

In this evaluation, an attempt was made to recognize the state in which the user is moving in the experimental building. Several chaise lounges were used in the experimental environment. The subject was asked to walk, move in a row, sit down, and stop. The subject in their twenties walked a specific route around the laboratory. The subject sat on a bench on the route, asked to change pace at any time, and was allowed to move his posture, stride, foot, etc. As a means of data collection, special sensor devices and sensors are not suitable for practical use;thus we used the common smartphone Nexus 5 for evaluation. The smartphone is put in the pocket of the pants in consideration of the burden on the user.

4.2 Estimation accuracy of models and optimization results of PDR

For the feature quantities of the test data, the weighting factors in each classifier were added up. The result of the classifier with the largest weighting factor value was adopted as the final estimation result. The weighting factor for the feature value changed with each learning;thus 10 classifiers were created for each label, and the weighting factor values were summed. In order to compare the estimation accuracy using multiple classifiers performed by the proposed method, the case of using a single classifier is compared. The results of using a single classifier and the F value of each class of the proposed method (with or without state transition) are shown in the table, and the accuracy rate of each method is shown.(1)

Table 1. f-Number of classifiers.

Context	Conventional method	Proposed method
Walk	0.45	0.80
Moored walk	0.33	0.76
Stop	0.36	0.70
Sit	0.21	0.80
Sit_down	0.64	0.72
Stand_up	0.74	071

When a single discriminator was used the window width was set to 250 ms, and sufficient features (steps 1 and 2) of walking and mooring walk cannot be obtained. The identification accuracy of stand and sit motions were high, but the state identification accuracy was low. However, in the proposed method that created two classifiers, gait etc. could be captured by other classifiers. Moreover the features could be captured, and the classification rate of the state could be improved. Therefore, the method using classifiers with different window widths was effective, but the state transition did not improve the estimation accuracy that much. This is considered to be caused by a mistake, which caused an erroneous transition by giving priority to the triggering of the leaving / sitting motion. Therefore, it is thought that a mechanism such as a transition pending state is needed so that it does not immediately transition when coming and going sitting behavior comes in the future, and decides the transition by looking at some subsequent estimation results.The experiment for DDR was conducted with the route and behavior as shown in the FIG3.

As a result, compared to the conventional method, the step detection error and the direction estimation error at the time of stopping, sitting, and moored walk are reduced(Fig4). During the stop, while the user is seated, the proposed method does not move almost at all, and the moored walk has few positioning errors due to a step estimation error. In the case shown in the figure, the effect looks small because it is a short time experiment, but it can be said that it is

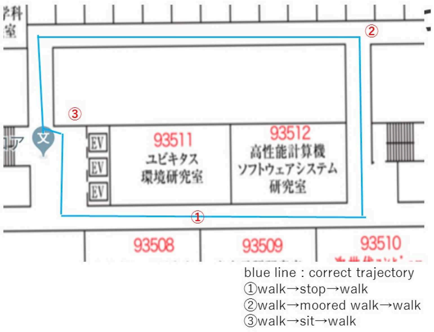

Fig. 3. Walking motion for the evaluation experiment

necessary to optimize according to the user's state like the proposed method, assuming long time use.

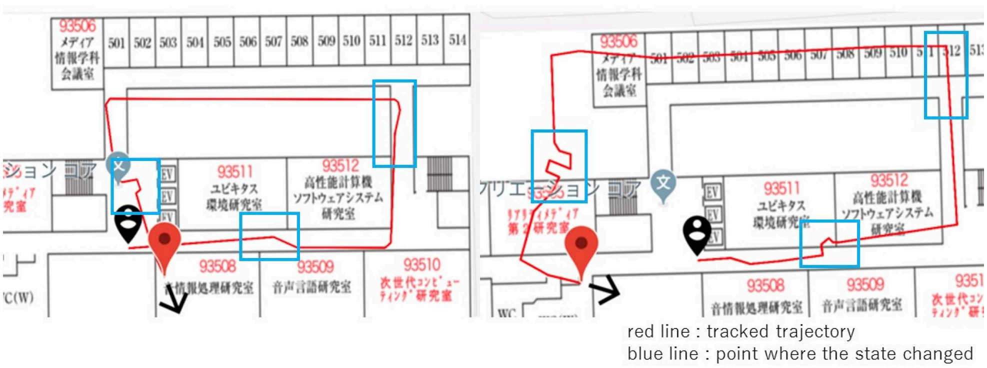

Fig. 4. Tracked trajectory(left:proposed method, right:conventional method)

5 Conclusion

This study proposed a method that used sensor data such as acceleration and angular acceleration that are commonly used in conventional PDR technology to detect characteristic daily walking patterns and movements,judge the user's condition and use PDR. We proposed DDR to optimize the algorithm and reduce the positioning error. Our future tasks aim to utilize this method in the actual environment(e.g.offices) improve the estimation accuracy of the classifier, and add motions and states to be identified. As a state to be added, we think about the movement to the side where the direction and movement direction of the body are different, and the movement to the rear. The PDR operates with the same movement direction as the direction of the body, these movements cannot be distinguished from normal walking, which causes positioning errors. We also aim to discover new issues by operating the proposed method in an environment closer to the actual usage environment.

Acknowledgement

References

1. Shun Yoshimi, Kohei Kanagu, Masahiro Mochizuki, Kazuya Murao, and Nobuhiko Nishio. Pdr trajectory estimation using pedestrian-space constraints: Real world evaluations. In Adjunct Proceedings of the 2015 ACM Interna- tional Joint Conference on Pervasive and Ubiquitous Computing and Proceed- ings of the 2015 ACM International Symposium on Wearable Computers, Ubi- Comp/ISWC'15 Adjunct, pp. 14991508, New York, NY, USA, 2015. ACM.
2. PARK, So Young; JU, Hojin; PARK, Chan Gook. Stance phase detection of multiple actions for military drill using foot-mounted IMU. sensors, 2016, 14: 16.
3. Koji Makita, Masakatsu Kourogi, Tomoya Ishikawa,Takashi Okuma, and Takeshi Kurata. PDRplus: HumanBehaviour Sensing Method for Service Field Analysis,pp. 25f30. Springer Japan, Tokyo, 2014.
4. Ling Pei, Robert Guinness, Ruizhi Chen, Jingbin Liu,Heidi Kuusniemi, Yuwei Chen, Liang Chen, and Jyrki Kaistinen. Human behavior cognition using smartphone sensors. Sensors, Vol. 13, No. 2, pp. 1402f1424, 2013.
5. D. Coskun, O. D. Incel, and A. Ozgovde. Phone posi-tion/placement detection using accelerometer: Impact on activity recognition. In 2015 IEEE Tenth In- ternational Conference on Intelligent Sensors, Sensor Net- works and Information Processing (ISSNIP), pp. 1f6, April 2015.
6. Khan, Adil Mehmood, et al. Activity recognition on smartphones via sensor-fusion and kda-based svms. International Journal of Distributed Sensor Networks, 2014, 10.5: 503291.
7. QIAN, Jiuchao, et al. Continuous motion recognition for natural pedestrian dead reckoning using smartphone sensors. In: Proceedings of the 27th International Technical Meeting of the ION Satellite Division, ION GNSS. 2014.
8. TIAN, Qinglin, et al. An enhanced pedestrian dead reckoning approach for pedestrian tracking using smartphones. In: Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP), 2015 IEEE Tenth International Conference on. IEEE, 2015. p. 1-6.
9. KANAGU, Kohei; TSUBOUCHI, Kota; NISHIO, Nobuhiko. Colorful PDR: Colorizing PDR with shopping context in walking. In: Indoor Positioning and Indoor Navigation (IPIN), 2017 International Conference on. IEEE, 2017. p. 1-8.
10. S. O. H. Madgwick, A. J. L. Harrison, and R. Vaidyanathan. Estimation of imu and marg orientation using a gradient descent algorithm. In 2011 IEEE Inter- national Conference on Rehabilitation Robotics, pp. 1f7, June 2011.