Proceedings of ICServ2013, pp.19-22 (2013)

PDRplus: human behaviour sensing method for service field analysis

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Abstract

This paper presents a novel method of estimating position, orientation, and multiple actions of a worker in a service field. In general, Pedestrian Dead Reckoning (PDR) is appropriate for effectively estimating the position and orientation of a pedestrian in an indoor environment. However, in actual service fields, PDR is not as accurate for workers' behaviour sensing when a number of actions for their work other than walking are taking place. Moreover, common sensors for PDR have less information for multiple action recognition other than walking. For realizing human behaviour sensing for service process analysis, we propose a method which integrates human localization and action recognition with the complementary use, named "PDRplus". In service fields, since position, orientation, and action of a human usually show strong correlation with her or his situation, both the PDR and action recognition can be improved with complementary use of the PDR and action recognition. In this paper, in order to ensure the effect of the complementary use of the PDR and action recognition, we conducted two types of experiments in real service industry fields. First we compared accuracies of the action recognition both with and without using the PDR in the restaurant kitchen, and average recognition rate of five types of actions was improved about 19 percentage points. Secondly, we compared accuracies of the PDR both with and without using the action recognition in house-assembly plants, and average position error was reduced by 19.5 %.

Keywords:
Pedestrian dead reckoning, Action recognition, Boosting, Service engineering

1 INTRODUCTION

It is obvious that continuous effort on service process improvement is very important for providing excellent service in actual service fields. In industrial fields, workers' log (position, orientation, operation, etc.) is tremendously useful in Kaizen approach[1] that includes changing the operations and monitoring the effect, then adjusting the improved operations. The workers' log is usually recorded manually to acquire reliable data. We believe this kind of Kaizen approach is also useful and effective for service process improvement. Therefore, our research team is conducting a research on 'Service Process Re-Engineering' that is a service process improvement approach based on measured and recorded human behaviour as a service providing process. However, in many actual service fields, it is undesirable and uncomfortable for the customers and the service providers that some investigating staff is plainly recording something. Therefore, we have been conducting research[5] on a framework that can automatically estimate and record workers' position and orientation. In this research, Pedestrian Dead Reckoning (PDR), which is a method that estimates the relative positions of a human, is used because it can be applied for indoor environment such as factories or service fields where Kaizen approach would be applied to[2][3][7]. However, the PDR can not detect actions other than walking. Moreover, because a worker is not always engaged in walking, other actions often have an adverse effect on positioning accuracy of the PDR. Hence, in this paper, we propose "PDRplus", a method which integrates PDR and action recognition with the complementary use[8]. For related researches[2][10], the contribution of this paper is simultaneous and complementary estimation of position, orientation, and actions of a human.

The remainder of this paper is organized as follows. In Section 2, we provide an overview of PDRplus, and in Section 3, we describe difficulties on the recognition of multiple operations and our approach to get over them. Section 4 presents the results of an experiment using the proposed method, and Section 5 offers our conclusions.

2 PDRPLUS

Dead reckoning is a method for estimating relative position and orientation based on the measured values of inertial measurement unit (IMU), using initial position and orientation in order to estimate absolute position and orientation. Inertial navigation systems that are used in airplanes, submarines and so on are commonly based on a dead reckoning method with double integral of very accurate acceleration sensor data. However, output of the small and lightweight sensors that people can wear without having an excessive load is not accurate enough to be used for measuring the position with double integral, and they are also impacted by noise. Thus, in the case of applying dead reckoning to a human, the simple approach is not able to be used. It is desirable to improve the estimation accuracy using several other methods in addition to the integration process. In view of this, PDR[2][3][7]: techniques for the measurement of position and orientation based on dead reckoning that focuses on human walking motion detection have been developed. The PDR works well for application systems such as human-navigation systems which user is mainly walking during using the system. However, as mentioned before, the positioning accuracy of the PDR is often getting down in working situation. For service field analysis, action of the worker is also essential for the behaviour sensing. However, multiple action recognition normally needs more sensors[9] than PDR, and not suitable for the workers in many service fields.

Figure 1 shows a conceptual diagram of PDRplus. PDRplus is a method for simultaneously estimating position, orientation, and actions of a human. We introduce data-stabilization using a tracking of gravity force direction for estimating movement acceleration. Since position, orientation, and action of a human usually show strong correlation with her or his situation, it is predicted that both the PDR and action recognition can be improved with complementary use. Therefore, we propose PDRplus, in which complementary localization and multiple action recognition are carried out iteratively, and results are finally integrated to output the estimation of position, orientation, and action of a human.

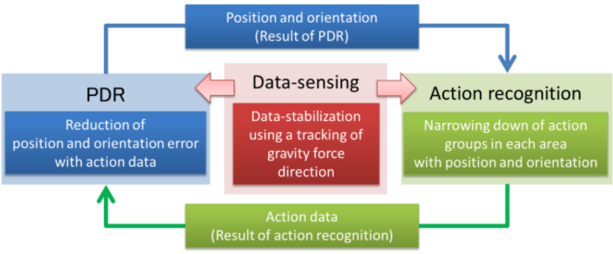

Figure 1: Concept of PDRplus

3 RECOGNITION OF MULTIPLE ACTIONS

In order to estimate a specific action, it is necessary to find out features of sensors' data that are commonly present in the positive samples. When clear differences in the samples are seen in the angular velocity and the acceleration data, recognition of the specific action can be performed by creating a simple classifier. For example, with the aim of recognizing human walking, recognition may become possible by looking for a specific wave pattern. In practice, though, the multiple general action recognition is often difficult with intuitively understanding the difference between the positive and negative samples. The main reasons for this are discussed below.

First, since human walking includes a specific repeatability in the angular velocity and the acceleration data, recognition of each step in the walking can be often realized with detecting the local minimum and maximum[6]. However, since general actions normally do not have such kind of repeatability, it is difficult to intuitively find out the typical pattern in the angular velocity and the acceleration data. Secondary, even several data of the same action are observed and compared, they are usually not so similar than the data of human walking. Because motions before and after the action to be detected affect the angular velocity and the acceleration data. Moreover, an action that is defined by a same word has often has varying patterns in terms of physical movement and time length.

For these reasons, in this study, boosting[4] with several features that are robust in deviations of movement patterns and time length is employed. Boosting is a type of supervised learning algorithm that uses input data with given ground truth. It is a technique for creating a classifier that has a high accuracy (a strong classifier) via the combination of several classifiers with low accuracy (weak classifiers). In boosting, because evaluation values of weak classifiers are automatically optimized, it is easy to simultaneously apply different types of data. Moreover, an additional advantage of employing boosting is that it becomes easy to incorporate new sources of information, such as information obtained from specific environments or from the additional wearable sensors. On the other hand, since the boosting algorithm assumes an unbiased variance of learning samples, the number and variance of the learning samples significantly affects the estimation results. The difference in estimation results due to the number of samples for the learning is described in Section 4.3, based upon the results of comparative experiments.

4 EXPERIMENT

In order to confirm the improved accuracy of both PDR and action recognition using the proposed method, three types of experiments were performed. First experiment was conducted with pre-arranged action data for learning, and accuracies of PDR with and without the action recognition were compared. Though details of the first experiment are shown in [8], it is summarized in this section for comparison purpose. Second and third experiments were conducted without pre-arranged action data, because it is normally difficult for actual industrial fields to prepare the pre-arranged action data only for the learning process.

Experimental conditions

The experiments were conducted in three types of environments; an office building, a restaurant kitchen, and house-assembly plants. In these experiments, our original sensor module (with a built-in magnetic sensor, angular velocity sensor, and acceleration sensor) was attached to the waist of each subject, and recorded the angular velocity and the acceleration of the subject. We have already developed a method for tracking the front direction of the body and the direction of the gravitational acceleration for the PDR, so sensor data stabilized to the coordinate system defined by these two directions are used for action recognition. For experiments in the office building, we used an acceleration sensor (ST micro, LIS3LV02DQ), angular velocity sensor (Epson Toyocom, XV-3500CB), and magnetic sensor (Asahi KASEI, AK8975). In the kitchen and assembly plants, we used the same acceleration and magnetic sensors, and used an Epson Toyocom, AH-6100LR as the angular velocity sensor. The experiments performed in each environment are described below.

4.1 Experiments in office building

In the office building, we conducted two experiments with two male workers who mainly performed desk work. First we defined ten kinds of actions that occur frequently during the regular work of an office worker, and created 50 sets of ground truth data based on the actual performance of the pre-defined actions by them. Next, we learned the true value data using AdaBoost, which is a specific type of boosting, and created a strong classifier for the detection of each action (details of feature values for weak classifiers are described in [8]). Since AdaBoost is basically a technique to create a strong classifier for binary identification of input data, in this experiment, we learned each action and created 10 types of strong classifiers. Table 1 presents a list of the actions, and average recognition rates for each action as the cross-validation results. Next, we applied the PDR process with action recognition. In this experiment, the PDR was carried out by one of the two subjects, and walking distance was approximately 254 meters. The distance between the final estimated position and the actual position was measured as the error. It should be noted that the test motion sequences included all 10 types of actions during walking. As a result, in the case in which action recognition was not used, there was an error of approximately 10.9 m (4.3% error for the entire walking distance), and in the case in which action recognition was used, the error was approximately 5.2 meters (2.0% error for the entire walking distance).

Table 1: Action Recognition rate (%)

Type of Action	Recognition Rate (positive)	Recognition Rate (negative)
1 step to the right	96.2	100.0
1 step to the left	95.4	100.0
1 step backward	94.2	99.6
1 step forward	99.6	100.0
Getting up from a chair	98.5	100.0
Sitting on a chair	99.6	99.6
Walking forward	92.3	99.4
Going up stairs	94.4	94.4
Going down stairs	93.6	99.2
Stooping down	99.4	100.0

4.2 Experiments in the restaurant kitchen

The following two experiments were carried out in a restaurant kitchen, with an employee on duty who was actually in charge of the cooking.

Creation of ground truth data of actions with sensor data obtained during the actual working

First, five types of actions were defined as recognition targets: “walking”, “vigorous action while standing” (lifting material, serving food, etc.), “stable action while standing” (cutting food, etc.), “up-and-down motion” (bending, crouching, etc.), and “stationary”. The sensor module was attached to the waist on the rear of the subject using a belt. Additionally, a video camera was installed at a position from where it would be possible to shoot the main work area of the employee, and a video was recorded lasting approximately seven hours. Ground truth data of defined actions were manually created by watching the video and recording the “start time”, “end time”, and “type of action”. The number of samples obtained for each type of action were: “walking”: 157, “vigorous action while standing”: 147, “stable action while standing”:19, “up-and-down motion”: 61, and “stationary”: 24 samples.

Action recognition using PDR

Weak and strong classifiers for action recognition were created with learning the ground truth data of each action. In this experiment, we created weak classifiers that focused on the acceleration and on the position data from the PDR, and created a strong classifier using these weak classifiers. The classifiers that were created in this experiment are detailed below.

We first created three types of weak classifiers using the acceleration data, and one type using the position data. Table 2 lists the feature values of the weak classifiers. Next, in order to verify how much the accuracy of the action recognition using the positioning data is improved, we created two groups of strong classifiers, one group includes classifiers comprised of only weak classifiers using the acceleration, and the other group includes classifiers comprised of weak classifiers using the acceleration and weak classifiers using the position data. Each group includes five classifiers for each action.

Then, we applied these two groups of strong classifiers to the training data. Since boosting could not be used in this experiment due the time consumed by the experiment, the degree of reliability of all the weak classifiers using acceleration was fixed at the same value. Then, the degree of reliability of the weak classifiers using position data was optimized so as to make the recognition rate for the learning sample the lowest. Finally, we compared the output values of the five types of strong classifiers, and performed action recognition by selecting an action that has maximum value (one-vs-rest method). In addition, in order to conduct a comparative evaluation of the effect of applying the PDRplus framework, the following three kinds of experiments were conducted in this evaluation; the proposed technique which uses A: only acceleration, B: only motion acceleration, and C: motion acceleration and position data. Table 3 shows the results of the experiments. Since technique C used the PDRplus framework and utilized both stabilization of the sensor and positioning data, compared with the results of techniques A and B, the variation in the accuracy rate during its operation was suppressed. The average accuracy rate for all five types was improved about 19 percentage points between the technique B and C.

Table 2: Feature values used in the creation of weak classifiers (three classifiers above are created with acceleration data, and the bottom classifier is created with position data).

Maximum observed value
Minimum observed value
Difference between maximum and minimum observed values
Distribution of positions of occurrence of each action included in true value data

Table 3: Action Recognition Rate (%)

	Walking	Vigorous action while standing	Stable action while standing	Up-down action	Abeyance	Average
Acceleration	69	73	69	10	20	48
Motion Acceleration	87	89	63	3	4	49
Motion Acceleration + Position Data	57	75	84	54	71	68

4.3 Experiment in a house-assembly plant

The following experiments were carried with one male worker who actually works in a house-assembly plant.

Action Recognition

Since the subject often nails during the work and the shock seems to affect to the positioning accuracy of the PDR, the target action for recognition in this experiment was set as “nailing”. A built-in sensor module placed inside a soft case was attached to the waist on the front of the subject. In addition, since the subject often had to walk around during the work, a cameraman followed him with a video camera and recorded the overview of actions for approximately one hour. The ground truth data of the action were manually created by watching the video and recording the “start time”, “end time” and “type of action”. A total of 666 positive and negative samples of nailing were created. We then learned the ground truth data using AdaBoost, just as we did in the case of the experiments in the office building, and created a strong classifier to detect the action of nailing. Table 4 lists the feature values that were used in the creation of weak classifiers. Finally, in order to verify the accuracy of the strong classifiers that had been created, the 666 pieces of data were divided into two groups. One group comprised 564 pieces of data to be used as training data, and the second group comprised 102 pieces that were test data as target of the estimation.

The recognition accuracy of the strong classifier for the test data was then calculated. In order to observe the difference in recognition accuracy due to differences in the number of training data, two types of strong classifiers were created: one type based upon a total of 188 training data, and a second type based upon a total of 564 training data. The recognition accuracy in both cases was then compared. In addition, when creating position data using the results obtained for action recognition, the recognition accuracy of “walking” is important. Hence, in this experiment, we created 235 pieces of data in which the correct action was “walking”, and compared the accuracy obtained with the case that includes judgment based on a strong classifier that recognizes “nailing”.

The results of the experiment are shown in Table 5. By increasing the number of training data, it was observed that the recognition rate for the action of “nailing” was improved. On the other hand, in the dataset in which the true value of the action was "walking", the recognition rate was as high as 90% with the use of any strong classifier, the performance of all classifiers being roughly equivalent. This result shows that, although the negative sample of "nailing" included several actions (including "walking", of course), when the correct action was "walking", there was a high probability of it being recognized as "not nailing".

PDR using action recognition

For the measured time of approximately 5 minutes, three types of positioning data were created: Method A: applying true value data of the action, Method B: applying the results of action recognition, and Method C: no action data. In Method B, the results of recognizing the action of "nailing" with the strong classifier created from the learning of 564 pieces of data (data that did not include the five minutes of creating positioning data) was applied. Next, in order to evaluate the accuracy of the position data, 11 occasions were selected by noting on the video when the position of the subject could be determined, at 15-seconds intervals. The true value data for the position of the subject were then created, and the error in the position data was evaluated. The results showed that the average error on each of the 11 occasions was about 6.8 m using method A, about 7.4 m for method B, and about 9.2 m for method C. Thus an average position error was reduced by 19.5 % between the method C and B. Finally, Figure 2 shows an example of the transition in the position error while the subject was engaged in nailing, in which the change in position is within the range of around one step. We would note that in this data, the position of the subject at 0 second elapsed time was initialized using the information of the RFID tag[5] attached to the environment, was considered to be the correct position. While the error in Method C is large, the divergence between the degree of error in Methods A and B is suppressed, since the position data is created so as not to change the position of the subject when the nailing action is recognized.

Table 4: Feature values used to create weak classifiers

Presence of a pattern less than -Θ after exceeding +Θ
Presence of a pattern exceeding +Θ after being less than -Θ
Presence of a pattern less than 0 after exceeding +Θ
Presence of a pattern exceeding 0 after being less than -Θ
Size of the Mean Crossing Rate
Size of the Zero Crossing Rate
Magnitude of the sum of squares
Percentage of Edge (The point at which there is a large difference between the observed values before and after the action)

Table 5: Action Recognition rate (%)

	Positive sample "Nailing" (sample size: 102)	Negative sample "Nailing" (sample size: 102)	Positive sample "Walking" (sample size: 235)
"Nailing" (sample size: 188)	59.8	75.5	90.6
"Nailing" (sample size: 564)	64.7	81.4	90.2

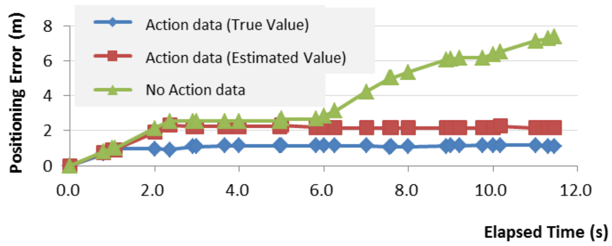

Figure 2: Examples of transition in positioning data error

5 CONCLUSION

This paper has proposed "PDRplus", a method which integrates human localization using PDR and action recognition with the complementary use. As a first step in the realization of "PDRplus", this paper presents experimental results that show the improved accuracy of position data that uses action recognition, as well as the improved accuracy of action recognition that was obtained using position data of PDR. As regards future work in action recognition, it would be desirable to create more generic classifiers to reduce the cost of creating training data. In PDR part, more active use of action recognitions (for instance, position correction to the stairs when "going up" or "going down" is detected) should be added. Finally, as regards future work in Kaizen approach, we will also attempt experiments for investigating relations between layout architecture of the environment and position, orientation, and action data.

Bibliography

[1] Imai, M.:"Kaizen - The Key to Japan's competitive success", McGraw-Hill, New York, NY (1986).

[2] Woodman, O. and Harle, R.:"Pedestrian localisation for indoor environments", In Proc. of the 10th Int. Conf. on Ubiquitous computing (UbiComp) (2008).

[3] Judd, T. and Vu, T.:"Use of a New Pedometric Dead Reckoning Module in GPS Denied Environments", In Proc. IEEE/ION Position, Location and Navigation (PLANS2008), pp.120-128 (2008).

[4] Freund, Y. and Schapire, R.E.:"A decision-theoretic generalization of on-line learning and application to boosting", Computational Learning Theory: Eurocolt, pp.23-37 (1995).

[5] Ishikawa, T., Kourogi, M. and Kurata, T.:"Economic and Synergistic Pedestrian Tracking System with Service Cooperation for Indoor Environments", International Journal of Organizational and Collective Intelligence, Vol.2, No.1, pp.1-20 (2011).

[6] Jin, Y., Toh, H.S, Soh, W.S. and Wong, W.C.: "A Robust Dead-Reckoning Pedestrian Tracking System with Low Cost Sensors", In Proc. IEEE Int. Conf. on Pervasive Computing and Communications (Percom), pp.222-230 (2011).

[7] Kourogi, M. and Kurata, T.: "Personal Positioning Based on Walking Locomotion Analysis with Self-Contained Sensors and a Wearable Camera", In Proc. ISMAR2003, pp.103-112 (2003).

[8] Kourogi, M., Ishikawa, T., and Kurata, T.: "A Method of Pedestrian Dead Reckoning Using Action Recognition", In Proc. IEEE/ION Position, Location and Navigation Symposium (PLANS), pp.85-89 (2010)

[9] Bao, L., and Intille, S. S.: "Activity Recognition from User-Annotated Acceleration Data", In Proc. of the 2nd Int. Conf. on Pervasive Computing, pp.1-17 (2004)

[10] Lester, J. Choudhury, T., and Borriello, G.: "A Practical Approach to Recognizing Physical Activities", In Proc. of Pervasive '06, pp.1-16 (2006).