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A Method of Pedestrian Dead Reckoning Using Action Recognition

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Abstract— **We present a method of estimating the location and orientation of a pedestrian which simultaneously recognizing his/her actions with a single low-cost inertial measurement unit (IMU) mounted at the waist of the user. Some of the actions other than walking locomotion, such as standing up from/sitting down on a chair, and bending over to slip through obstacles, taken by the pedestrians can be mostly seen at the particular locations where the objects and building facilities to induce the actions are placed. Conversely, by knowing the current location and its attribute about possibly taken actions, the action recognition process can be improved with the contextual information since prior knowledge about occurrence of actions is given as the attribute in the map. Additionally, when the posture (such as sitting, standing and getting to one knee) of the pedestrians is known, falsely recognized actions can be rejected. Experimental results show that accuracy of the action recognition on six types of the action (forward walking, backward walking, side stepping, sitting down on/standing up from a chair, going downstairs/upstairs and bending over) is more than 95% by cross validation test on the training data set, and the results also show that error rate of the PDR localization is reduced from 4% of the walking distance to 2% in the total scenario within the office environment by using the results of action recognition to adjust the estimated location.**

Keywords: Pedestrian dead reckoning (PDR), action recognition, machine learning, AdaBoost

I. INTRODUCTION

It is strongly desired to not only acquire the location and orientation but also recognize the actions of working staffs in many fields of the service and manufacturing industries such as restaurants, nursing care, accommodations and building maintenance to improve their efficiency and productivity. In such fields where the staffs are frequently moving around, it is important to understand flow lines of each staff and their actions on the lines, since such information provides crucial hints on improvement of the works by visualizing and analyzing the flow lines with actions. Since improvement of efficiency and productivity of staffs in the labor-intensive works significantly reduces the operating cost, it has a great impact on the total cost.

It is promising approach to use self-contained sensors (accelerometers, gyroscopes, and magnetometers) to detect and measure movement of the working staffs because the patterns of acceleration and angular velocity of human locomotion are typical. Inertial measurement units (IMUs) are packaged products of these sensors, and they are widely available from high-end to low-end. However, high-end IMUs are unlikely to be equipped by the working personnel due to their size and weight jamming the operation.

In this paper, we take an approach of pedestrian dead reckoning (PDR) exploiting the strict constraints found in human locomotion, and realize PDR implementation by a single low-cost IMU equipped with the waist, which also enable us to recognize several types of actions simultaneously.

Our contribution is to show that (1) location and orientation of a pedestrian can be estimated, and the actions can be recognized by processing sensor data from a single low-cost IMU, (2) localization accuracy can be improved by action recognition with use of a machine learning framework and (3) the action recognition mechanism can be refined by the estimated location and orientation with map information.

II. RELATED WORKS

The pedestrian dead-reckoning or PDR-based methods are deeply studied in many previous works, and are found promising to estimate location and orientation of persons as pedestrians. Furthermore, since the constraints of movement found in pedestrians can be exploited, low-cost IMUs are proven to be sufficient for such applications.

The PDR-based methods can be categorized into two approaches by the equipped positions of the IMUs shown in the following:

- Shoe-mounted PDR [1][2]
- Waist-mounted PDR [3][4]

In the shoe-mounted PDR approach, the IMUs are equipped in shoes or boots to exploit the constraint such that the part of the body becomes still while it touches the ground. Since the IMU's velocity is known to be zero for these moments, zero velocity updates or ZUPTs can be executed to cancel the accumulated error. Recent trends in PDR research seem to favor this approach because of the ZUPTs. However, it is difficult to detect and recognize several types of actions with little movement of feet such as standing up from/sitting down to a chair, and taking a load from the ground, which can play crucial roles in many applications.

On the other hand, in the waist-mounted PDR approach, the IMUs are equipped with the waist of the user, which is near the center of gravity of the human. Since the movement of the center of the gravity is empirically known to be typical, this approach uses the techniques of pattern recognition to detect and measure walking locomotion. Although it is difficult to execute ZUPTs unlike the shoe-mounted PDR approach, it has advantage to sense the actions with movement of the center of the gravity including walking locomotion. The waist-mounted PDR approach enables us to estimate location and orientation of pedestrians and to recognize the actions by using the single IMU.

III. PDRPLUS

We have developed both software and hardware for the method of waist-mounted PDR to mainly target the domain of service and manufacturing fields [5].

A. *The prototype hardware system*

We produced prototypes of IMU with a barometer and radio frequency identification (RFID) tag reader (shown in Figure 1 and Table I). The gyroscopes used in this IMU are calibrated in terms of offset drift caused by the temperature change acquired by the thermometer placed near each gyroscope.

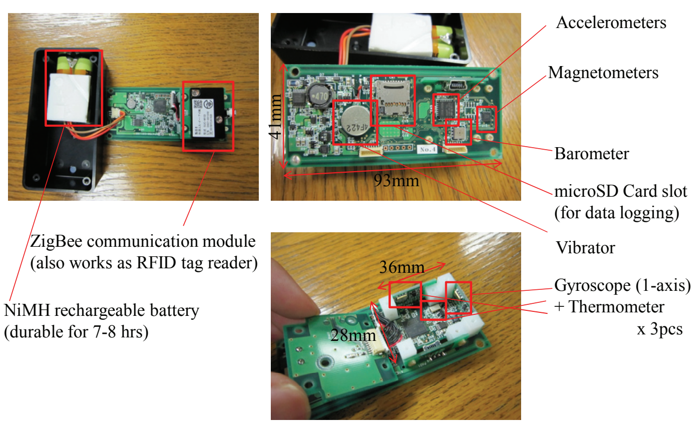

Figure 1. The prototype IMU.

TABLE I.
SENSORS USED IN THE PROTOTYPE IMU.

Type of sensors	Manufacturer / model number
Accelerometers (3-axis)	ST micro, LIS3LV02DQ
Gyroscope (1-axis)	Epson Toyocom, XV-3500CB
Magnetometers (3-axis)	Asahi KASEI, AK8975
Thermometers	Analog Devices, TMP36
Barometer	Bosch, BMP085

B. *Requirements for PDR system*

The waist-mounted PDR system is required to have functions to detect and discriminate each mode of walking, that are (1) forward walking and going upstairs/downstairs, (2) side stepping, and (3) backward walking. Additionally, we aim at realizing recognizing several types of actions with movement of the center of the gravity of the body. The result of action recognition is used to adjust the estimated location.

We have used Kalman filtering framework to fuse different source of information on the location [8]. However, if we try to exhaustively exploit the constraints (walls, obstacles, elevators and stairs) in the map, other tracking framework such as the particle filter is preferable. We expand our system to use the particle filter framework to fuse many types of localizing and orientating information from surveillance cameras and RFID tags [7].

C. *The Process of PDRplus*

The diagram of PDRplus process is shown in Figure 2. As described earlier, output of gyroscopes combined with thermometers are compensated before being fed into the attitude estimator run by extended Kalman filtering (EKF). In the EKF framework, bias components of accelerometers and gyroscopes are being tracked with the reference of earth magnetic field (EMF). However, magnetometers are not always capable of sensing EMF due to existence of local disturbance. We therefore test the magnetic fields obtained from the magnetometers in terms of their inclination and magnitude estimated from the EMF model such as World Magnetic Model (WMM). Acceleration vector and angular rate vector are converted into the human-centric local coordinate system, and then fed into action recognition process where several types of actions are classified. Since some of the actions can take place on the limited area, the location of the user can be acquired. Conversely, by knowing the location some of the action misclassified by the process can be rejected simply because the action cannot take place in the proximity of the estimated location. Detailed information about the action recognition process is described later in Section IV.

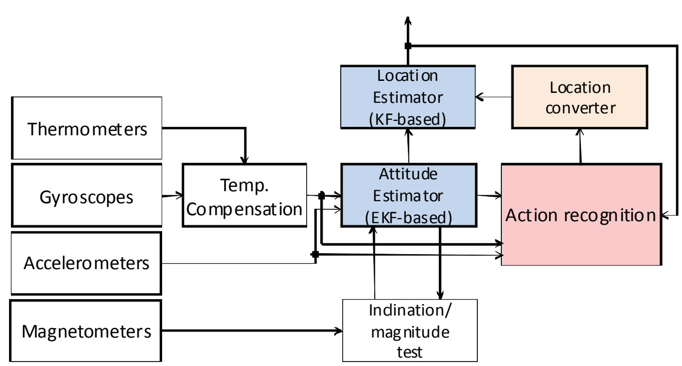

Figure 2. The diagram of PDRplus.

IV. METHODOLOGIES

In this section, we describe a detailed method of action recognition from the sensor data acquired by the waist-mounted IMU. We also describe a method of localization combined with results of action recognition.

A. *The machine learning technique*

Adaptive boosting or AdaBoost is one of the algorithms in machine learning [6], which uses a weighted combination of the insufficiently accurate classifiers called weak classifiers (which must have error rates of less than 50%) to gain the single final accurate classifier called the strong classifier.

B. *Input data set fed to AdaBoost for training*

Since sensor data of acceleration and angular rate are based on the IMU-body frame and thus they contain local information about movement, it is likely to be inappropriate to directly feed them into the machine learning algorithm. Hence, we use nine data set processed beforehand in the following: (1) the acceleration along with the gravity (2) acceleration along with the forward direction (3) acceleration along with the sideway direction, (4) angular rate around the gravity-axis, (5) angular rate around the forward direction axis, (6) angular rate around the sideway-axis, and (7)-(9) the gravitation vector (3-axis), as a data set for AdaBoost. We also use frequency-domain feature of the input data on (1)-(6) shown above.

C. *The weak classifiers for boosting*

Before considering candidates for the weak classifiers, we examine the patterns of acceleration and angular rate found in various mode of walking and the targeted actions. Figure 3 shows the patterns of acceleration along with sideways found in motion of single left side-stepping.

One of the typical patterns in acceleration is from zero to the positive peak, and then to the negative peak. Although existence of this pattern does not necessarily means the occurrence of walking locomotion or other actions, finding the pattern gives us the error rate of less than 50%.

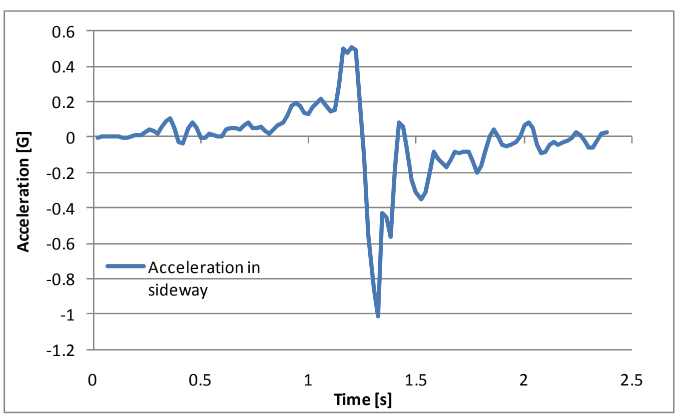

Figure 3. Acceleration along with the sideway in side-stepping.

Features in the time domain recognized by the weak classifiers used in the AdaBoost training are listed in the following:

- The value is going up above the threshold ($+\theta_1$) and then down below the threshold ($-\theta_1$).
- The value is going down below the threshold ($-\theta_2$) and then up above the threshold ($+\theta_2$).
- The value is going up above the threshold ($+\theta_3$) and returns to zero level.
- The value is going down below the threshold ($-\theta_4$) and returns to zero level.
- The deviation from the average is going up above the threshold ($+\theta_5$) and down below the threshold ($-\theta_5$).
- The deviation from the average is going down below the threshold ($-\theta_6$) and up above the threshold ($+\theta_6$).
- The time difference between the time of maximum value is between the ($c_7-\theta_7$) and ($c_7+\theta_7$).
- The time difference between the time of minimum value is between the ($c_8-\theta_8$) and ($c_8+\theta_8$).
- Cross correlation value between the two sequences is between ($c_9-\theta_9$) and ($c_9+\theta_9$).
- Cross correlation value between the two sequences is above the threshold ($+\theta_{10}$).

We also use features in the frequency domain listed below:

- The ratio between the maximum power frequency and the total power is above the threshold ($+\theta_{11}$).
- The phase difference of the maximum power frequency between the two sequences is between ($c_{12}-\theta_{12}$) and ($c_{12}+\theta_{12}$).

D. *The training data set used for AdaBoost*

We prepare the training data set for AdaBoost learning on six types of actions: forward walking (of single step and of successive steps), backward walking (single), side stepping (single, left and right), sitting down to/standing up from a chair, going downstairs/upstairs (single and successive) and bending over. The data set also contains motion in non-walking mode. The total number of labels on the data set is 11 as shown in Table II.

TABLE II.
TYPES OF ACTION TO BE RECOGNIZED.

Label	The type of motion
1	Right side stepping (single step)
2	Left side stepping (sing step)
3	Backward walking (single step)
4	Forward walking (single step)
5	Standing up from a chair (single action)
6	Sitting down to a chair
7	Forward walking (successive steps)
8	Going upstairs (successive steps)
9	Going downstairs (successive steps)
10	Bending over (single action)
11	Non-walking

V. EXPERIMENTAL RESULTS

We conducted experiments to test the performance of the proposed method of action recognition and the total accuracy of the proposed system of the PDR with the action recognition.

A. Experimental conditions

The sensor data (3-axis acceleration, 3-axis magnetic field, and 3-axis angular rate) is captured at the sampling rate of 50 Hz by our prototype IMU, and transferred via wireless communication channel (with ZigBee) and then stored in a remote computer. While the stored data is handled in the off-line manner, its real-time processing by less computationally powerful computer such as embedded computing system is plausible. We use 50 training data set for each action shown in Table II, and therefore use 550 data set in total.

The attitude of the IMU in the world coordinate system is estimated by our previously proposed method [4][8]. By using the estimated attitude, acceleration and angular velocity can be converted into the person-oriented data.

B. The error rate of action recognition

The training data set (11-labeled, 50 data set for each label) is prepared for cross validation. The recognition rates on each action are summarized in Table III, IV, V, VI, VII and VIII.

TABLE III.
RECOGNITION RATE ON INPUT VS OUTPUT
FOR LEFT AND RIGHT SIDE-STEPPING TRAINING DATASET

	Positive	Negative
Positive	95.4%(L)/96.2%(R)	0%(L)/0%(R)
Negative	4.6%(L)/3.8%(R)	100%(L)/100%(R)

TABLE IV.
RECOGNITION RATE ON INPUT VS OUTPUT
FOR SINGLE FORWARD AND BACKWARD WALKING TRAINING DATASET

	Positive	Negative
Positive	99.6%(F)/94.2%(B)	0%(F)/0.4%(B)
Negative	0.4%(F)/5.8%(B)	100%(F)/99.6%(B)

TABLE V.
RECOGNITION RATE ON INPUT (TOP) VS OUTPUT (LEFT SIDE)
FOR STANDING UP FROM/SITTING DOWN TO A CHAIR TRAINING DATA SET

	Positive	Negative
Positive	98.5%(U)/99.6%(D)	0%(U)/0.4%(D)
Negative	1.5%(U)/0.4%(D)	100%(U)/99.6%(D)

TABLE VI.
RECOGNITION RATE ON INPUT (TOP) VS OUTPUT (LEFT SIDE)
FOR GOING UPSTAIRS/DOWNSTAIRS TRAINING DATA SET

	Positive	Negative
Positive	94.4% (U)/93.6%(D)	0.6%(U)/0.8%(D)
Negative	5.6%(U)/6.4%(D)	99.4%(U)/99.2%(D)

TABLE VII.
RECOGNITION RATE ON INPUT (TOP) VS OUTPUT (LEFT SIDE)
FOR SUCCESSIVE FORWARD WALKING TRAINING DATA SET

	Positive	Negative
Positive	92.3%	0.6%
Negative	7.7%	99.4%

TABLE VIII.
RECOGNITION RATE ON INPUT (TOP) VS OUTPUT (LEFT SIDE)
FOR BENDING OVER TRAINING DATA SET

	Positive	Negative
Positive	99.4%	0%
Negative	0.6%	100%

C. Total performance on accuracy of the PDR localization

We conduct four test runs (total distance: 254 meters) in an office environment to estimate location by the proposed PDRplus system. In the test run, the subject is taking all actions shown in Table II. The map information is prepared beforehand to adjust estimated location by the PDRplus system. This information contains the location of stairs and obstacles to be avoided by bending over.

The result of the accuracy of the PDRplus localization is summarized in Table IX. The action recognition can also be benefited from the localization process since several types of actions can only be occurred in specific region in the map. While walking along with the flat corridor, detection of going upstairs or downstairs by the action recognition can be rejected and thus performance of action recognition is slightly improved as shown in Table X.

TABLE IX.

COMPARISON OF LOCALIZATION ACCURACY BY PDRPLUS AND PDR ONLY.

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The localization method	Error in location [m]
PDRplus	5.2 m (2.0%)
PDR only	10.9 m (4.3%)

TABLE X.

COMPARISON OF RECOGNITION RATE BY THE ACTION RECOGNTION WITH PDRPLUS AND THE ACTION RECOGNITION ONLY.

	Recognition rate
Action recognition with PDRplus	97.5%
Action recognition only	94.4%

VI. CONCLUSION

We have developed a method of PDR localization using action recognition based on the AdaBoost techniques. Since the method can recognize walking locomotion (and its detailed mode)/non-moving status, its accuracy on the PDR estimated location is much improved. By combining with the map information, the followings can be achieved: (1) PDR estimation of location can be adjusted, (2) the action recognition method can be improved by the fact that the specified actions are likely to take place at the fixed positions.

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