2010 IEEE International Conference on Robotics and Automation
Anchorage Convention District
May 3-8, 2010, Anchorage, Alaska, USA

Person Identification by Integrating Wearable Sensors and Tracking Results from Environmental Sensors

Tetsushi Ikeda, Hiroshi Ishiguro, Dylan F. Glas,
Masahiro Shiomi, Takahiro Miyashita, and Norihiro Hagita

Abstract— **To provide personal and location-dependent services in public spaces such as shopping malls, it is important to be able to estimate the positions and identities of people in the environment. Sensors in the environment reliably detect their current positions, but it is difficult to identify people using these sensors. On the other hand, signals from wearable sensors can be used to identify people correctly, but precise position estimation remains problematic. In this paper, we describe a novel method of integrating laser range finders (LRFs) in the environment and wearable inertial sensors. Time sequences of angular velocities estimated from both LRFs and wearable sensors are matched to identify people. Examples of tracking individuals in the environment that confirm the effectiveness of this method are shown.**

I. Introduction

PRECISE location information in public spaces provides useful cues for many kinds of services. One important application type is security services that identify and locate people in the environment. Another is information services that provide personal and location-dependent information to a mobile information terminal. For location-dependent applications, the technical challenge is to locate a specific person carrying a mobile information terminal in a crowded environment.

Since many people carry cellular phones with them in their daily lives these days, and cellular phones are becoming powerful mobile information terminals, a location system that uses cellular phones is realistic for a public information infrastructure. In this paper, we propose a method that locates people carrying a mobile device precisely and continuously.

In ubiquitous computing, many kinds of wearable devices have been used to locate people. Since a location system using ID tags requires the installation of many reader devices in the environment for precise localization, it is unrealistic to use it in large public spaces. Wearable inertial sensors are also used to locate people, but the cumulative error in estimation is often problematic. For a precise location system, it is important to integrate other sources of information.

Location systems using sensors installed in the environment have also been studied. For example, location systems using cameras and laser range finders (LRFs) can track people in the environment very precisely. However, it is difficult to locate a person carrying a specific wearable device by using only environmental sensors.

For the problem of locating a person who has a specific mobile device, a promising and realistic approach is to integrate environmental sensors that observe people from the environment and wearable sensors that observe the person carrying them. In this paper, we propose a novel integration method of LRFs in the environment and wearable gyroscopes and accelerometers to locate people precisely and continuously. Since location systems using LRFs are successfully applied for tracking people in large public spaces like a train station and the size of each LRF is becoming smaller, LRFs are appropriate for installing in public spaces. Since cellular phones are expected to have inertial sensors for many kinds of applications, users who have a cellular phone do not have to carry any additional devices.

The rest of this paper is organized as follows. First, we review relevant literature about locating people. Then, we discuss a method of integrating environmental and wearable sensors and how it can provide reliable estimation. Finally, we discuss the application of our method to a practical system and present the results of an experimental evaluation.

II. Related Works

There are three approaches to locating people in an environment: using environmental sensors, using wearable devices, and using a combination of both types.

A. Locating People using Environmental Sensors

Person position location has frequently been studied in computer vision [9]. One advantage of using cameras is that we can use a lot of information including colors and motion gestures. A problem with cameras is that they suffer from changes in the lighting conditions in the environment.

LRFs have recently attracted increasing attention for locating people in public places. Since they have become smaller, it is now easier to install them in environments. Since LRFs observes only the positions of people, installation of LRFs does not raise privacy issue. Cui et al. [4] succeeded in tracking a large number of people. Glas et al. [6] placed LRFs in a shopping mall to predict the trajectories of people.

In general, sensors placed in the environment are good at locating people precisely. However, it is difficult to use them to identify people when they are walking in a crowded

Manuscript received September 15, 2009. This work was supported by KAKENHI (21118003).

Tetsushi Ikeda, Hiroshi Ishiguro, Dylan F. Glas, Masahiro Shiomi, Takahiro Miyashita, and Norihiro Hagita are with ATR-IRC Laboratories, Kyoto 619-0288, Japan. e-mail: ikeda@atr.jp.

Hiroshi Ishiguro is with the Department of Systems Innovation, Graduate School of Engineering Science, Osaka University, Osaka 565-0871, Japan.

environment.

B. Locating People by Using Wearable Sensors

In ubiquitous computing, wearable devices have been used to locate people [8]. Devices that have been studied include IR tags [16], ultrasonic wave tags [7], RFID tags [1] [14], Wi-Fi [2], and UWB [12]. If the device ID is registered with the system, the person carrying that specific device can be located and identified. However, tag-based methods require the placement of many reader devices in order to locate people accurately, so the cost of installing reader devices is problematic in large public places. Wi-Fi- and UWB-based methods do not provide enough resolution to distinguish one person in a crowd. Furthermore, if users of the system have to carry additional devices just to use the location service, the cost and inconvenience should also be considered.

Wearable inertial sensors have also been used to locate a person by integrating observations [3] [5] [8]. Since integral drift has been problematic, it is important to combine observations with those of other sensors. Recently, a few types of cellular phones have started to incorporate inertial sensors, and some people are carrying them in their daily lives. Therefore, using inertial sensors for locating people is a promising approach.

C. Locating People by Using a Combination of Sensors

To locate and identify people in the environment, combination methods that integrate both environmental sensors and wearable devices have been studied.

Kourogi et al. [11] integrated wearable inertial sensors, a GPS function, and an RFID tag system. Woodman and Harle [18] also integrated wearable inertial sensors and map information.Schulz et al. [15] used LRFs and ID tags to locate people in a laboratory, and they proposed a method that integrates positions detected using LRFs and identities people by using sparse ID-tag readers in the environment. Mori et al. [13] used floor sensors and ID-tags and identified people carrying ID tags. These methods focused on gradually identifying people after initially locating their positions roughly using ID tags when they approached reader devices. However, since these methods integrate environmental sensors and ID tags on the basis of their positions, it is difficult to distinguish them in a crowded environment.

In contrast, our method integrates them on the basis of the motion of people. We use LRFs and wearable inertial sensors to observe the angular velocity of a person's body. Then, the person carrying a specific device is located by selecting the sequence of positions that has the most similar angular velocity. Since our method uses motion-based integration, it does not suffer from the drift problem of inertial sensors.

III. People Tracking and Identification by Using Environmental and Wearable Sensors

To locate each person who is carrying wearable sensors, we focus on angular velocity signals around the vertical axis that are observed from environmental and wearable sensors.

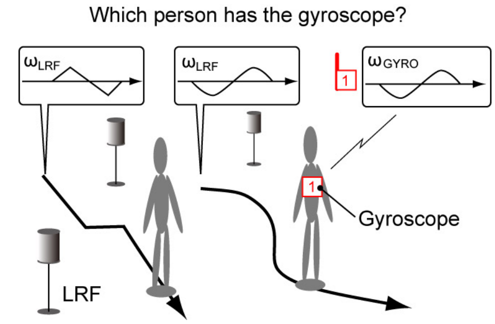


Figure 2. Locate a person carrying a specific wearable device by matching wearable and environmental sensors

After angular velocity is observed from two types of sensors, signals are compared to determine whether two signals come from same person.

In this framework, the problem of locating the person with a wearable sensor is to compare the signal from the wearable sensor to all signals from the people detected by environmental sensors and selects the person with the most similar signal (Figure 1).

A. Locating People and Estimating Angular Velocities by Using Environmental Sensors

Our method expands upon the system described in [10] and uses a particle-filter-based algorithm to track people in the environment (Figure 2). In our tracking algorithm, a background model is first computed for each sensor by analyzing hundreds of scan frames to filter out noise and moving objects. Points detected in front of this background scan are grouped into segments within a certain size range and ones that persist over several scans are registered as human detections.

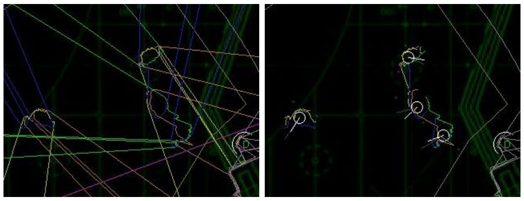
Each person is then tracked by the particle filter using a linear motion model. Likelihood is evaluated on the basis of the potential occupancy of each particle's position. For example, humans cannot occupy spaces that have been observed to be empty.

A straightforward way of computing angular velocity from the detected positions is:

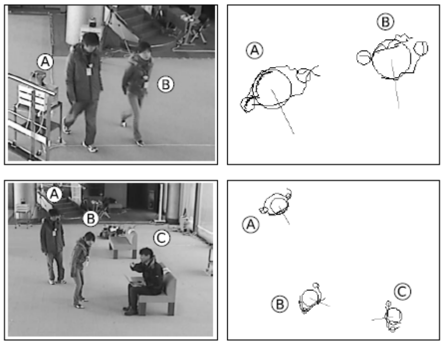
$$\mathbf{v}(t) = (\mathbf{x}(t) - \mathbf{x}(t-1)) / \Delta$$
$$\theta(t) = \arg(\mathbf{v}(t))$$
$$\omega(t) = (\theta(t) - \theta(t-1)) / \Delta,$$

where $\mathbf{v}, \mathbf{x}, \theta, \omega$ are velocity vector, position vector, direction, angular velocity, respectively, and Δ is the sampling period.

In general, the position and angular velocity of a person can change independently. However, when people walk in daily lives, changes in angular velocities could be mainly caused by changes of the walking directions. In fact, we found angular velocity estimated by using LRFs are similar to that observed by using wearable gyroscopes (Figure 3).



a) Observations by LRFs b) Estimated positions of people



c) Examples of scenes and estimation results

Figure 2. Person position estimation using LRFs

B. Estimating Angular Velocities by Using Wearable Inertial Sensors

The angular velocities around three axes are observed for each person by using body-mounted 3-axis gyroscopes. Only the angular velocity around the vertical axis is used, and this is computed as $\omega_G = \boldsymbol{\omega}_G \cdot \mathbf{e}_z$, where $\boldsymbol{\omega}_G$ is the observed angular velocity vector and $\mathbf{e}_z$ is the unit vector of the vertical axis. In principle, $\mathbf{e}_z$ is estimated by integrating the angular velocity signals [17], but the drift error grows with time. Therefore, we use accelerometers and compute the short-time average of the observation to estimate $\mathbf{e}_z$:

$$\hat{\mathbf{e}}_z = -\frac{1}{Lg}\sum_t^L \mathbf{a}(t),$$

where $\mathbf{a}$ is the acceleration vector and g is the gravitational constant. In the experiments, we set the length L to the number of samples for 10 s.

Though this estimation is incorrect when people are walking, it does not suffer from drift error. In preparatory experiments, we confirmed that this simple averaging can be used to estimate $\mathbf{e}_z$ for our purpose.

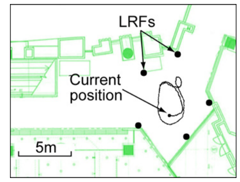
When body motion is measured using inertial sensors, the sensor's attachment position is important. In preparatory experiments, we tested three different attachment positions: on the head, chest, and waist. We found that the results for the head-mounted sensor were noisy, while the results for the other positions were adequate and almost the same. In the following experiments, the inertial sensor was placed on the person's chest.

C. Integration by Matching Time Sequence of Angular Velocity from Both Sensors

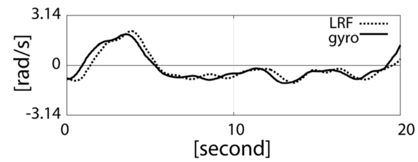
Then, the location of the person carrying specific gyroscope is computed by selecting the trajectory that minimizes the difference between time sequences of angular velocity between two sensors:

$$c^{(j)} = \sum_{t=1}^{T} |\,\omega_G(t) - \omega_L^{(j)}(t)\,|, \tag{1}$$

where $\omega_G(t)$ is the angular velocity of the specific person estimated from his/her gyroscope, and $\omega_L^{(j)}(t)$ is the angular velocity of person j estimated from the LRFs.



a) Trajectory



b) Angular velocity

Figure 3. An example signals from LRFs and a gyroscope in 20 seconds. a) Estimated trajectory using LRFs. b) Estimated angular velocities. The vertical axis is the angular velocity. Two signals are quite similar.

Smoothed angular velocity signals for 20 s from LRFs and from a gyroscope are shown in Figure 3. Though these signals were observed from different viewpoints, they are quite similar.

Since observing a body's angular velocity by using a gyroscope is straightforward and free from drift error and since positions are estimated precisely using environmental sensors, our method enables a robust and precise localization.

IV. SENSOR INTEGRATION CONSIDERING CONFIDENCE IN OBSERVATION

A. A Probrem of Estimating Angular Velocity using Position Sensors

The simple method of comparing angular velocities (Eq. (1)) does not always provide reliable results. Angular velocities estimated using LRFs and gyroscopes are shown in Figure 4. In the data for 20 s, the estimated angular velocities differed significantly when the person stopped and changed direction. This difference arises because the error in the angular velocity estimated using LRFs is larger when the velocity is low. In general, when a target's angular velocity is estimated using position-observing sensors, the confidence in the estimated value depends on the target's velocity. Typical changes in confidence while estimating direction are shown in Figure 5. When the position is observed with a certain precision, the direction is estimated from the difference between the subsequent positions. The estimated direction is limited to a certain distribution according to the target's velocity (Figure 5 (a)). However, if the velocity is low, the distribution is broad and the confidence is low (Figure 5 (b)). Since angular velocity is estimated from the difference in directions, the confidence in the angular velocity also depends on the target's velocity. This causes a problem when we locate people on the basis of Eq. (1)

B. Evaluating Confidence in Observed Angular Velocity

When we observe positions by using sensors in the environment and estimate angular velocities, the confidence in the estimated angular velocity depends on the person's velocity. Since we cannot trust the estimated angular velocity when the velocity is low, a simple matching method using Eq. (1) will fail to locate the person carrying a wearable sensor.

One approach for dealing with this problem is to consider the confidence in estimated angular velocity when matching angular velocities. To confirm the effectiveness of this approach, we introduce a simple cost function based on target's velocity.

C. Sensor Integration Based on Evaluating Cost Function

The cost function uses a simple heuristic but is a robust method of evaluating observation confidence. A weight term that depends on the target's velocity is added to Eq. (1):

$$c_2^{(j)} = \sum_{t=1}^{T} \frac{1}{\mathrm{var}(v)} \left| \omega_G^{(i)}(t) - \omega_L^{(j)}(t) \right|, \qquad (2)$$

where the term var() represents the variance of the estimated angular velocity, which depends on the target's velocity. In the following experiments, we approximated the variance of the angular velocity by using the simple formula:

$$\mathrm{var}(v) = \alpha \sin^{-1} \frac{\sigma_L}{v} , \qquad (3)$$

where σ_L is the fixed standard deviation of the position sensor's estimation error and α is a constant set to the value for which var is 1.0 for the average velocity. As shown in Figure 6, Eq. (3) is based on simple geometrical estimation.

V. EXPERIMENTS

A. Experimental Setup

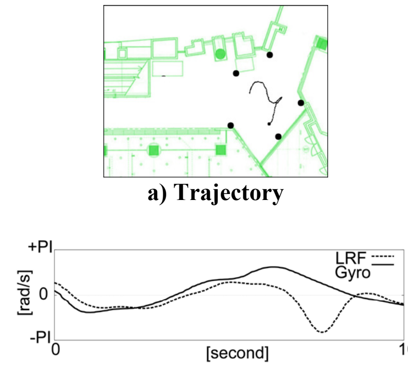
We conducted experiments in an entertainment/shopping arcade located near the entrance to Universal Studios Japan, a major theme park. We located people in a 20-m-radius area of the arcade containing shops selling clothing and accessories on one side and an open balcony on the other side. People in this area were monitored via a sensor network of consisting of five SICK LMS-200 LRFs mounted at a height of 85 cm (Figure 7). We expanded the system in [10] by integrating wearable sensors to locate and identify people.

Each person in the environment was detected and tracked with a particle filter. By computing the expectation of the particles, we estimated the position and velocity 25 times per second. This tracking algorithm ran very stably and reliably with a measured position accuracy of less than 6 cm for our environment [6].

Two people in the environment each carried one wearable sensor (WAA-006, ATR Promotions) with a three-axis gyroscope and a three-axis accelerometer (Figure 8). In the experiments, the observed angular velocity and acceleration signals were timestamped and sent to a host PC via Bluetooth.

Since our method locates people by comparing angular velocity time sequences, it is important to adjust the clocks of the LRFs and wearable sensors. In the following experiments, the wearable sensor clocks were synchronized with the host PC when they initially established a Bluetooth connection.

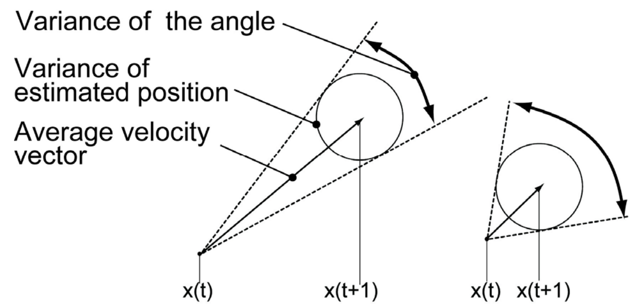
Another problem is the delay in the transmission from the wearable sensors to the host PC. In the following experiments, signals were sent with timestamps added by the wearable



a) Trajectory

b) Angular velocity

Figure 4. Example of signals produced for a low walking speed. a) Trajectory in 10 s. The person stopped once and changed direction. b) Estimated angular velocity signals differed significantly when the person stopped.



a) Larger velocity **b) Smaller velocity**

Figure 5. Relationship between the target's velocity and the variance of the estimated angle.

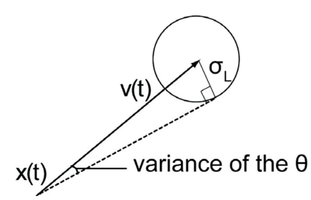


Figure 6. Estimation of variance of the direction based on the observed position.

Figure 7. Experimental environment in a shopping mall. Circles indicate the installed LRF network (left). SICK LMS-200 LRF (right)

Figure 8. Wearable sensor device used in the experiments (left). The sensor was attached to the person's chest (right).

sensors. If the timestamp were set after the signals had been sent (e.g., by the host PC), the results would be affected by sudden transmission delays.

B. Estimated Angular Velocities of a Walking Person

The upper graph in Figure 9 shows the estimated angular velocity of a person who walked around in the environment while carrying an inertial sensor. The angular velocity was estimated by two different methods: using LRFs and using a gyroscope. The two estimates were similar and changed in a correlated manner except for a few times. The lower graph in Figure 9 shows the person's estimated walking speed. It is clear that significant differences between angular velocity estimates occurred only when the walking speed was very low (dashed circles in the lower graph).

C. The Effect of Introducing the Weight to the Cost Function

The effect of introducing our weight function is shown in Figure 10. The upper graph shows the cost function computed without the weight (based on Eq. (1)) and the lower graph shows the result computed with the cost function (Eq. (2)). In the upper graph, the two lines sometimes touch and this could be the cause of failures. The lower graph enables the person to be distinguished from other people much more clearly.

D. Identification of Target People based on Cost Function

Figure 11 shows clearly how our algorithm distinguished the person carrying an inertial sensor when there were many people in the environment. The graphs shows the computed cost function based on Eq. (2) between the sensor-equipped person and all the other people in the environment during a 20-s period. The number of lines represents the number of people: there were several people in the environment. The

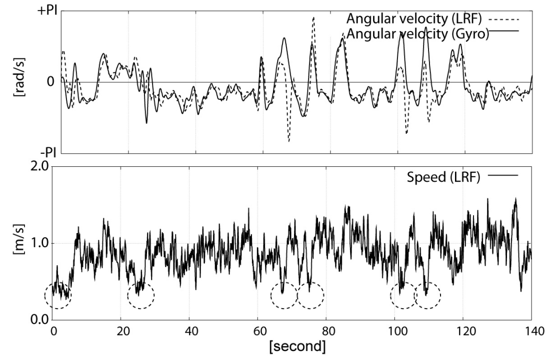
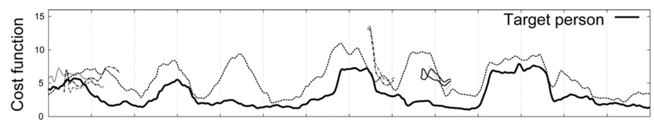
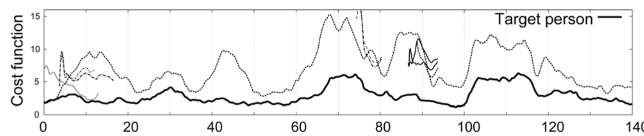


Figure 9. Upper graph: Angular velocity computed using LRFs (dashed line) and a gyroscope (solid line). Lower graph: Walking speed estimated using LRFs. When the person walks slowly (dashed circle in the lower graph), the angular velocity estimates differed significantly.



a) Without weight term (Eq. (1))



b) With weight term (Eq. (2))

Figure 10. Effect of introducing the weight term into the cost function. When the cost function was computed using the weight term (b), the person could be distinguished from other people very clearly.

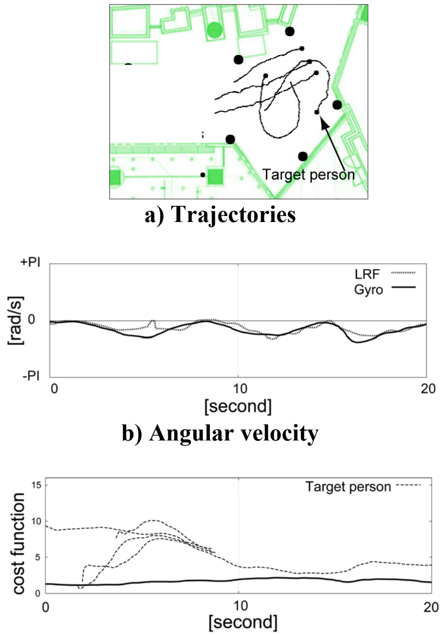
cost function of the target person (solid line) is clearly lower than those of the other people (dashed lines) in the environment. This means that the cost function was lowest for the target person, who could be located very precisely using the tracking system using LRFs.

E. Effect of the Length of Observations

Comparative results for various lengths of the computing cost function (parameter T in Eq. (2)) are shown in Figure 12. It was difficult to locate the person from only instant observation. When T was set to at least 100 frames (about 4 s), the person was located almost correctly. In the bottom graph in Figure 12, for which T was set to 200 frames (about 8s), the result is very clear.

VI. CONCLUSION

In this paper, we described a method for precisely locating a person carrying a wearable sensor device by integrating environmental and wearable sensors. We used a network of LRFs and wearable gyroscopes and accelerometers to compute the angular velocity of each person's body. By selecting from among the trajectories detected using LRFs the one minimizing the difference in angular velocity time



a) Trajectories

b) Angular velocity

c) Cost function

Figure 11. Results for locating a person carrying a wearable sensor in an environment containing several people. The upper graph shows the angular velocity estimates for the person: they are very similar. The lower graph shows the computed cost functions. The cost function of the person carrying the sensor was the lowest and this person was clearly located.

sequence, we could identify and precisely locate the person in the environment.

We considered the problem of estimating angular velocity from position-observing sensors, and we devised a weighted cost function that reflects the confidence in the angular velocity estimation.

Experimental results for locating people in a shopping mall show the precision of our method. Since LRFs are now becoming common and people are carrying cellular phones that contain inertial sensors, we believe that our method is realistic and can be a fundamental technique for location services in public places.

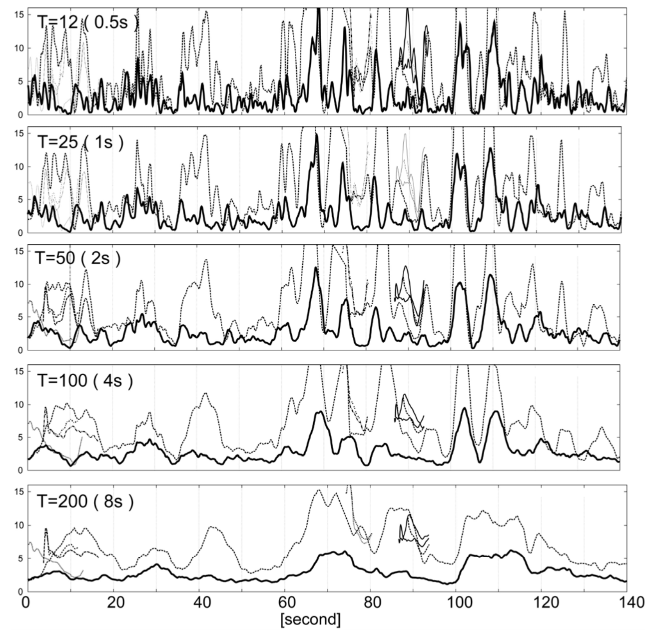


Figure 12. The cost function computed for different time period T. The costs are computed for all people detected using LRFs. The ID of gyroscope is associated to the trajectory with the lowest cost. These graphs represents results for T = 0.5, 1, 2, 4, 8 [s] from the top to the bottom.

REFERENCES

[1] T. Amemiya, J. Yamashita, K. Hirota, and M. Hirose., "Virtual leading blocks for the deaf-blind: A real-time way-finder by verbal-nonverbal hybrid interface and high-density RFID tag space.," In Proc. IEEE Virtual Reality Conf., 2004, pp. 165-172.

[2] P. Bahl and V. N. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system," Proc. of IEEE INFOCOM 2000, Vol. 2, 2000, pp. 775-784.

[3] L. Bao and S. S. Intille., "Activity recognition from user-annotated acceleration data," In Proc. of PERVASIVE 2004, Vol. LNCS 3001, A. Ferscha and F. Mattern, Eds. Springer-Verlag, 2004, pp. 1-17.

[4] J. Cui, H. Zha, H. Zhao, and R. Shibasaki., "Laser-based detection and tracking of multiple people in crowds," Computer Vision and Image Understanding, Vol. 106, No. 2-3, 2007, pp. 300-312.

[5] E. Foxlin, "Pedestrian Tracking with Shoe-Mounted Inertial Sensors," IEEE Computer Graphics and Applications, Vol. 25, Issue 6, 2005, pp. 38 - 46.

[6] D. F. Glas, T. Miyashita, H. Ishiguro, and N. Hagita, "Laser-Based Tracking of Human Position and Orientation Using Parametric Shape Modeling," in Advanced Robotics, Vol. 23, No. 4, pp. 405-428, 2009.

[7] A. Harter et al., "The anatomy of a context-aware application," In Proc. 5th Annual ACM/IEEE Int. Conf. on Mobile Computing and Networking (Mobicom '99), 1999, pp. 59-68.

[8] J. Hightower and G. Borriello., "Location systems for ubiquitous computing," Computer, Vol. 34, No. 8, 2001, pp. 57-66.

[9] W. Hu, T. Tan, L. Wang, and S. Maybank., "A survey on visual surveillance of object motion and behaviors," IEEE Trans. on Systems, Man and Cybernetics, Part C, Vol. 34, No. 3, 2004, pp.334-352.

[10] T. Kanda, D. F. Glas, M. Shiomi, H. Ishiguro, and N. Hagita, "Who will be the customer?: A social robot that anticipates people's behavior from their trajectories," In Proc. 10th Int. Conf. on Ubiquitous Computing (UbiComp '08), 2008, pp. 380-389.

[11] M. Kourogi, N. Sakata, T. Okuma, and T. Kurata, "Indoor/Outdoor Pedestrian Navigation with an Embedded GPS/RFID/Self-contained Sensor System," In Proc. 16th Int. Conf. on Artificial Reality and Telexistence (ICAT2006), 2006, pp.1310-1321.

[12] K. Mizugaki et al., "Accurate Wireless Location/Communication System With 22-cm Error Using UWB-IR," IEEE Radio & Wireless Symposium, pp. 2007, 455-458.

[13] T. Mori, Y. Suemasu, H. Noguchi, and T. Sato., "Multiple people tracking by integrating distributed floor pressure sensors and RFID system," In Proc. of IEEE Int. Conf. on Systems, Man and Cybernetics, Vol. 6, 2004, pp. 5271-5278.

[14] L. M. Ni et al., "LANDMARC: indoor location sensing using active RFID," Proc. of the First IEEE Int. Conf. on Pervasive Computing and Communications (PerCom 2003), 2003, pp. 407-415.

[15] D. Schulz, D. Fox, and J. Hightower, "People tracking with anonymous and id-sensors using rao-blackwellised particle filters," In Proc. 18th Int. Joint Conf. on Artificial Intelligence (IJCAI'03), 2003, pp. 921-928.

[16] R. Want, A. Hopper, V. Falcao, and J. Gibbons., "The active badge location system," ACM Trans. Inf. Syst., Vol. 10, No. 1, 1992, pp. 91-102.

[17] O. J. Woodman., "An introduction to inertial navigation," Technical Report UCAM-CL-TR-696, Univ. of Cambridge, 2007.

[18] O. Woodman and R. Harle., "Pedestrian localisation for indoor environments," In Proc. 10th Int. Conf. on Ubiquitous Computing (UbiComp '08), 2008, pp. 114-123.