PEDESTRIAN IDENTIFICATION BY ASSOCIATING WALKING RHYTHMS FROM WEARABLE ACCELERATION SENSORS AND BIPED TRACKING RESULTS

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Abstract: Providing personal and location-dependent services is one of the promising services in public spaces like a shopping mall. So far, sensors in the environment have reliably detected the current positions of humans, but it is difficult to identify people using these sensors. On the other hand, wearable devices can send their personal identity information, but precise position estimation remains problematic. In this paper, we propose a novel method of integrating laser range finders (LRFs) in the environment and wearable accelerometers. The legs of pedestrians in the environment are tracked by using LRFs, and acceleration signals from pedestrians are simultaneously observed. Since the tracking results of biped feet and the body oscillation of the same pedestrian show same walking rhythm patterns, we associate these signals from same pedestrian that maximizes correlation between them and identify the pedestrian. Example results of tracking individuals in the environment confirm the effectiveness of this method.

1 INTRODUCTION

Information infrastructure that provides personal and location-dependent services in public spaces like a shopping mall permit a wide variety of applications. Such a system will provide the positions of friends who are currently shopping in the mall. When they have many bags, users will call a porter robot, which can reach them by using the location system. To enable location-dependent and personal services, we propose a system that locates and identifies a pedestrian, who carries a mobile information terminal, anywhere in a crowded environment.

Many kinds of location systems have been studied that provide the positions of pedestrians by using sensors installed in the environment. For example, location systems using cameras and laser range finders (LRFs) can track people in the environment very precisely. However, it is difficult to identify each pedestrian or a person carrying a specific wearable device by using only sensors in the environment.

On the other hand, 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 not a realistic solution in large public spaces. Wearable inertial sensors are also used to locate people, but the cumulative estimation error is often problematic. For a precise location system, it is important to integrate other sources of information.

In order to locate a pedestrian carrying a specific mobile device anywhere in an environment, a promising approach is to integrate environmental sensors that observe people from the environment and wearable sensors that locate the person carrying them. In this paper, we propose a novel method integrating LRFs in the environment and wearable accelerometers to locate people precisely and continuously. Since location systems using LRFs have been successfully applied for tracking people in large public spaces like train stations and the sizes of LRF units are becoming smaller, LRFs are highly suitable for installation in public spaces. Since many cellular phones are equipped with an accelerometer for a variety of applications, users who have a cellular phone do not have to carry any additional

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device.

The rest of this paper is organized as follows. First, we review previous studies. Then, we discuss a method of integrating LRFs and accelerometers 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.

2 RELATED WORKS

2.1 Locating Pedestrians using Environmental Sensors

Locating pedestrian has been an important issue in computer vision and frequently studied (Hu et al., 2004). One advantage of using cameras is that we can use much information including colors and motion gestures. A problem with cameras is that they suffer from changes in the lighting conditions in the environment. Also, using cameras in public spaces for identification purpose sometimes causes privacy issue.

LRFs have recently attracted increasing attention for locating people in public places. As they have become smaller, it becomes 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., (2007) succeeded in tracking a large number of people by observing legs of pedestrians. Zhao and Shibasaki (2005) also track people by using a simple walking model of pedestrians. Glas et al., (2009) placed LRFs in a shopping mall to predict the trajectories of people by observing customers at the height of waist.

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

2.2 Locating People by using Wearable Sensors

In ubiquitous computing, wearable devices have been used to locate people (Hightower and Borriello, 2001). Devices that have been studied include IR tags (Want et al., 1992), ultrasonic wave tags (Harter et al., 1999), RFID tags (Amemiya et al., 2004); (Ni et al., 2003), Wi-Fi (Bahl and Padmanabhan, 2000), and UWB (Mizugaki et al., 2007). 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-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 (Bao and Intille, 2004); (Foxlin, 2005); (Hightower and Borriello, 2001). Since integral drift has been problematic, it is important to combine observations with those of other sensors. Recently, many types of cellular phones have started to incorporate accelerometers, and some people are carrying them in their daily lives. Therefore, the approaches using acceleration sensors for locating people can effectively use the infrastructure.

2.3 Locating People by using a Combination of Sensors

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

Kourogi et al., (2006) integrated wearable inertial sensors, a GPS function, and an RFID tag system. Woodman and Harle (2008) also integrated wearable inertial sensors and map information. Schulz et al. (2003) used LRFs and ID tags to locate people in a laboratory, and they proposed a method that integrates positions detected using LRFs and identifies people by using sparse ID-tag readers in the environment. Mori et al. (Mori et al., 2004) 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 as they approach 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 when the spatial resolution by using ID tags is not enough.

In contrast, we integrate LRFs in the environment and wearable sensors on the basis of the motion of people. Since our method uses the motion feature itself and does not incorporate the computation of precise position in the integration process, it does not suffer from the drift problem of inertial sensors.

In previous work (Ikeda et al., 2010), LRFs and wearable gyroscopes are integrated based on body rotation around the vertical axis from both types of sensors. However, it was difficult to distinguish pedestrians who move in a line when the trajectories are similar. Another problem is the method's use of gyroscopes, even though cellular phones equipped with gyroscopes are not yet so common.

In this paper, to cope with these problems, we propose a new method that extracts features from a bipedal walking pattern. LRFs observe pedestrians at the height of legs and estimate the positions of people and walking rhythms. The wearable accelerometer also observes walking rhythms. Since walking rhythms differ from person to person, the proposed method can distinguish pedestrians walking in a line, and it uses only an accelerometer in the wearable devices.

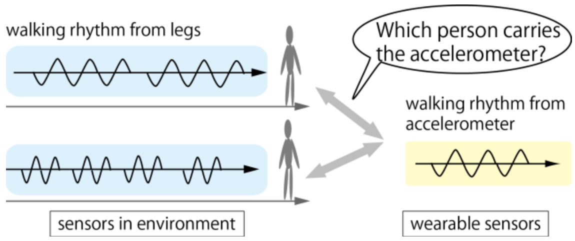
3 PEOPLE TRACKING AND IDENTIFICATION USING LRFS AND WEARABLE ACCELEROMETERS

3.1 Associating Walking Rhythm from LRFs and Wearable Accelerometer

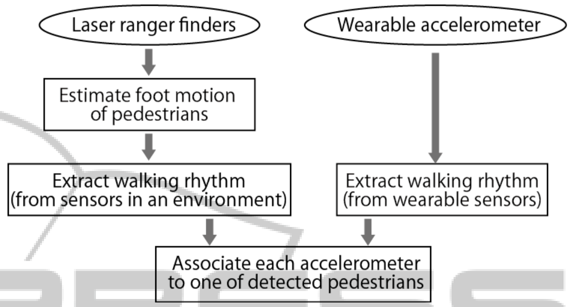
To locate each person carrying a wearable sensor, we focus on the walking rhythms that are observed from environmental and wearable sensors. After features of the walking rhythm are observed from the two types of sensors, signals are compared to determine whether the two signals come from the same person.

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

Legs of pedestrians are tracked by using LRFs in the environment, and the motions of both legs are estimated. Simultaneously, the timings of footsteps are observed by using wearable acceleration sensors. If the signals from both kinds of sensors are from the same pedestrian, we can assume that the two signals are highly correlated, since they were originally generated from a common walking rhythm. Figure 1 (b) shows the overview of the proposed algorithm.



a) Concept of the proposed algorithm.



b) Flow of the proposed algorithm

Figure 1: Locating a person carrying a specific wearable device by matching wearable and environmental sensors.

Figure 2: Pedestrian walking in a shopping mall. The white marks represent the detected legs of pedestrians. Walking rhythm of each pedestrian is observed using wearable accelerometer and LRFs by tracking at least one foot.

3.2 Tracking Biped Foot of Pedestrians by using LRFs

Zhao and Shibasaki (2005) proposed a pedestrian tracking method by using LRFs at the height of the legs. By observing the legs of pedestrians, not only the positions of pedestrians but also the timing of their footsteps was observed.

We also observe the legs at the height of 20cm by using LRFs. Our method expands upon the system described in (Glas et al., 2009) and uses a particle-filter-based algorithm to track legs 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 those that persist over several scans are registered as leg detections. Each leg is then tracked by the particle filter using a simple linear motion model. Examples of observed velocity of two legs are shown in Figure 3(b). Then the detected legs that satisfy the following constraints are clustered and considered a hypothesis of a pedestrian:

Constraint 1

1. At least one of the two feet is not moving.
2. The distance between the two feet is less than a threshold (100 cm in the experiments).

3.3 Observation of Acceleration from Wearable Sensors

To extract walking rhythm from the wearable accelerometer, we focus on the vertical component of the observed acceleration. Three-dimensional acceleration vector $\mathbf{a}(t)$ is observed and averaged over a few seconds (T is number of frames of eight seconds in the experiments) to estimate the vertical direction of the sensor. Then vertical acceleration $a_{\text{vert}}(t)$ is estimated as follows:

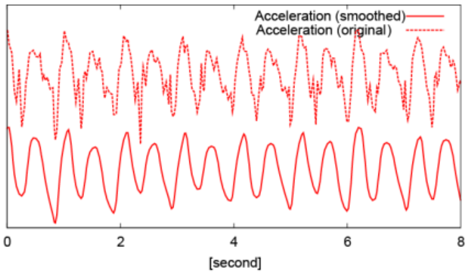
$$\tilde{\mathbf{a}}(t) = \sum_{\tau=1}^{T} \mathbf{a}(\tau)/T\,, \qquad (1)$$

$$a_{\text{vert}}(t) = \tilde{\mathbf{a}}(t) \cdot \mathbf{a}(t)\,. \qquad (2)$$

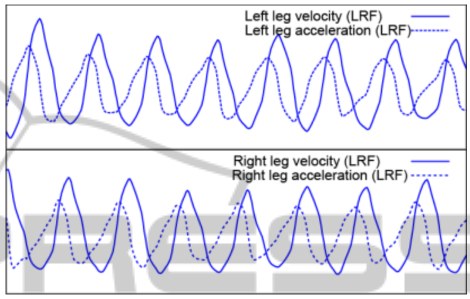
Original and smoothed vertical acceleration signals are shown in Figure 3 (a). The accelerometer is attached to the left waist. One footstep of the walk is about 500 milliseconds in the graph, and the timing of the footsteps of both legs is clearly observed. Note that since the accelerometer is attached to the left waist, the impact of a footstep of the left leg is clearer.

3.4 Associating Motion of Biped Foot and Acceleration Signal

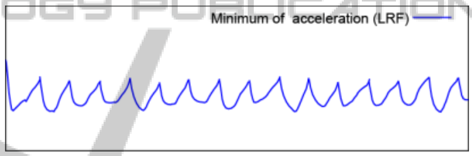
Figure 3 (b) shows the smoothed velocity and acceleration of each leg estimated by our tracking method. When the speed of a pedestrian's idling leg becomes lower and it finally lands on the ground, a large vertical acceleration is observed. Therefore, we can expect the impact of landing to be observed when the acceleration of the idling leg is negative. Note that since LRFs are observed at the height of the legs, the velocity does not become zero when the foot lands.



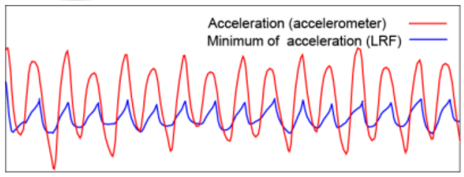
a) Vertical acceleration from wearable accelerometer. Dashed line shows original signals and solid line shows smoothed signal.



b) Velocity (solid line) and acceleration (dashed line) of left and right legs of a pedestrian from LRFs.



c) Minimum of acceleration of both legs from LRFs (Equation (4))



d) Superimposed signal (acceleration from accelerometer (a) and LRFs (c)). Signals from same pedestrian shows clear correlation. The vertical axis is adjusted to overlap both signals.

Figure 3: Examples of signals from LRFs and an accelerometer taken over eight seconds.

Figure 3 (c) shows the acceleration of both legs. The derivatives of velocities of legs (Figure 3 (c)) and the vertical acceleration signal (Figure 3 (a)) are highly correlated (Figure 3 (d)).

To evaluate the correlation between the two signals, we propose computing Pearson's correlation function between the minimum leg acceleration from LRFs and the acceleration from the accelerometer.

$$\rho(t) = \rho(a_{\text{vert}}(\tau), a_{\text{foot}}(\tau)) \qquad (3)$$

$$a_{\text{foot}}(t) = \min(a_{left}(t), a_{right}(t)))\,, \qquad (4)$$

where $a_{left}(t)$, $a_{right}(t)$ are acceleration of right and left leg. Note that when $a_{vert}(\tau), a_{foot}(\tau)$ are jointly Gaussian, mutual information between them is computed as

$$I(a_{vert}(\tau), a_{foot}(\tau)) = \frac{1}{2}\log\frac{1}{1-\rho(a_{vert}(\tau), a_{foot}(\tau))} \tag{5}$$

Hershey and Movellan (2000) first used this measure to integrate audio and vision to detect speaker. See (Cover and Thomas, 2006) for detail. Eq. (5) shows that our algorithm evaluates similarity of walking rhythms by computing mutual information between them.

3.5 Associating Motion of One Foot and Acceleration Signal

In a crowded scene, sometimes only one leg of a pedestrian is observed. To compute the correlation between the one leg and the acceleration signal, we use only a limited phase of the acceleration of LRFs since acceleration signal contains signals from both legs.

In computing Eq. (3), we define an activation signal for an acceleration signal to select the contribution of the acceleration from one leg. Figure 4 shows the steps to compute the activation signal. We compute the long-term average of a velocity signal and compute one maximum/minimum point in each range, indicating how much the original signal is larger/smaller than the average. The leg lands a little before the minimum point. Then a sequence of the time index of local maximum $t_{\max}(i)$ and local minimum $t_{\min}(i)$ is computed. Suppose $t_{\max}(i) < t_{\min}(i) < t_{\max}(i+1)$. Then the activation signal is defined as

$$\text{active}(t) = \begin{cases} 1 & t_{\max}(i) \le t < t_{\max}(i) + \frac{3}{4}(t_{\min}(i) - t_{\max}(i)) \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

and the summation in Eq. (3) is computed only when active(t)=1. The factor 3/4 is for extracting the range when the impact of landing is observed in accelerometer. Figure 5 shows the range that activation function is one. Correlation function Eq. (3) is computed for each trajectory of a single leg and each biped foot that satisfies Constraint 1. For example, in the case of Figure 3 (d), the activation signals is one at around every other lower peak of the acceleration signal.

Finally, for each wearable acceleration sensor, the position of the user is estimated by selecting a single leg or biped foot that maximizes correlation function Eq. (3).

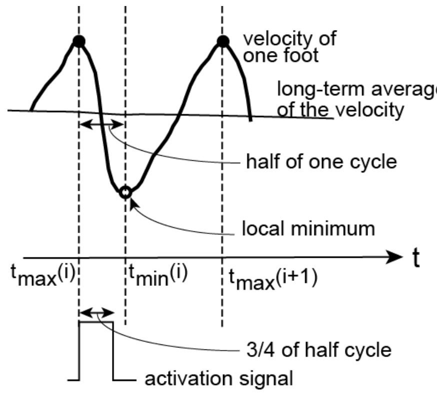


Figure 4: Estimated positions of pedestrians by tracking biped foot using LRFs.

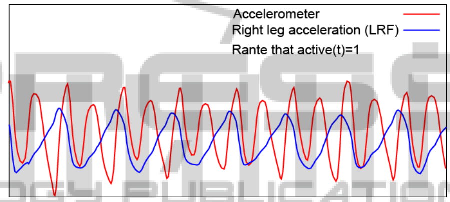


Figure 5: The range that activation function for a leg. In the range active(t)=1, the acceleration from both sensors correlated.

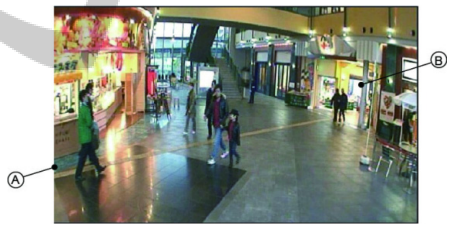
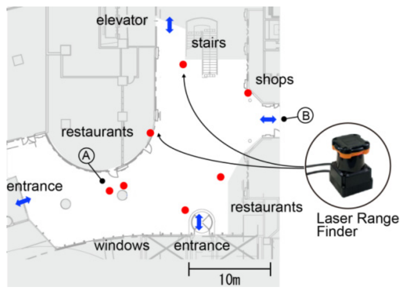


Figure 6: Experimental environment in a shopping mall.



a) Positions of LRFs (shown as red circles) in the experimental environment.

Model No.	Hokuyo Automatic UTM-30LX
Measuring area	0.1 to 30m, 270°
Accuracy	±30mm (0.1 to 10m)
Angular resolution	approx. 0.25°
Scanning time	25 msec/scan

b) Specifications of the LRF.

Figure 7: Experimental setup.

Model No.	ATR Promotions WAA-010
Weight	20 [g]
Size (W×D×H)	39×44×12 [mm]
Sampling frequency	500 [Hz]
Range	±2G
Interface	Bluetooth

Figure 8: Sensor devices used in experiments.

3.6 Selecting a Single Foot / Biped Feet that Maximizes Correlation between Signals

For each accelerometer, we compute correlation function for each tracked single legs by using activation function and each biped feet that satisfied the Constraint 1. The single foot or the biped feet that maximizes correlation function is a candidate of the pedestrian who carries the accelerometer.

The correlation function is not very stable when the number of samples are small. We compute correlation function for data samples of four seconds.

4 EXPERIMENTS

4.1 Experimental Setup

We conducted experiments at a shopping mall in the Asia and Pacific Trade Center, in Osaka, Japan (Figure 6). We located people in a 20-m-radius area of the arcade containing many restaurants and shops. People in this area were monitored via a sensor network consisting of seven LRFs installed at a height of 20 cm (Figure 7). We modified a previous system (Glas et al., 2009); (Kanda et al., 2008) for tracking a biped foot and expanded it to incorporate wearable sensors to locate and identify people. Figure 7 shows the area of tracking and positions of sensors.

Each leg of a pedestrian who enters the area 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. Figure 8 shows an example of tracking results of legs.

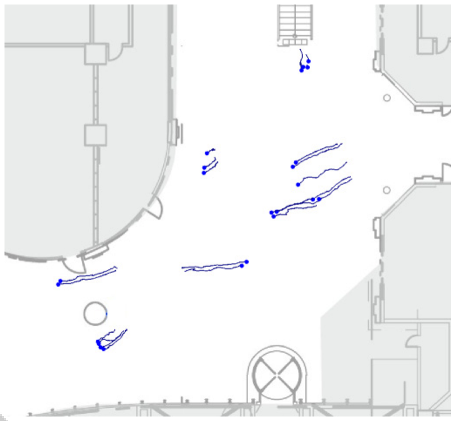


Figure 9: Estimated trajectories of feet in four seconds. There were 12 pedestrians in the period. The filled circles represent the latest positions. Sometimes only one feet of a pedestrians is observed because of the effect of occlusion.

In experiments, three subjects in the environment each carried one wearable sensor with a three-axis accelerometer (Figure 8). In the area of tracking, there are usually about 10 pedestrians at the same time who did not carry wearable sensor. So the number of the legs observed at a time is more than 20 (Figure 9). We repeated the experiments eight times in 12 minutes. For each acceleration signal from a wearable sensor, our algorithm estimated the trajectory of the owner. The observed acceleration signals were sent to a host PC via Bluetooth. We repeated the experiments four times.

Since our method locates people by comparing 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.

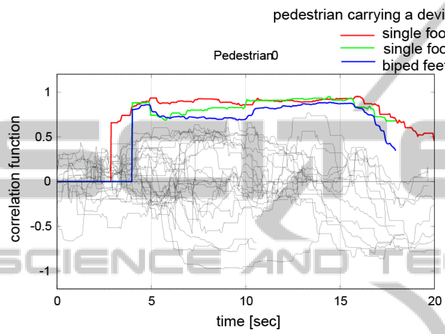
Another problem is the delay in the transmission from the wearable sensors to the host PC. In the following experiments, signals were sent with timestamps added by the wearable sensors. If the timestamp were set after the signals had been sent (e.g., by the host PC), the results would be affected by sudden transmission delays.

4.2 Computed Correlation for each Wearable Sensor

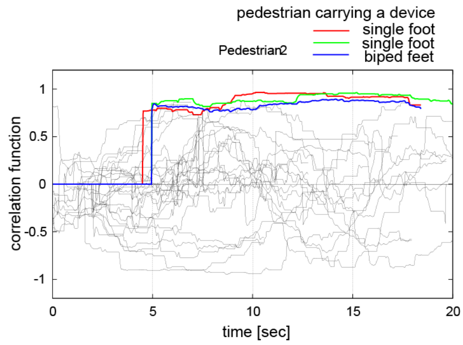
For each wearable device, correlation is computed based on equation (3), (4) between the acceleration signal from the wearable device and the sequences of all detected legs. The leg with the highest correlation is considered as the leg of the user who carries the wearable device.

Figure. 10 shows the computed correlation function between each wearable device of each subject and all detected legs. Solid line shows the correlation with user of the device, and they usually show the highest values compared with dashed lines that are from other pedestrians. We compute the correlation between signals in five seconds. Until five seconds has passed after the pedestrian appeared, the value is set to zero.

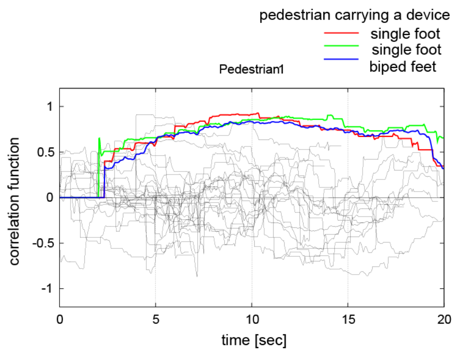
We tested with three subjects and four trial. In 12 experiments, the pedestrian who are carrying the sensor was been correctly estimated almost all time in the sequences.



a) pedestrian 1



b) pedestrian 2



c) pedestrian 3

Figure 10: Correlation function computed for acceleration signal between each wearable acceleration sensor and biped feet. Colored line shows correlation function of correct user. Number of users is three in the experiments.

5 DISCUSSION

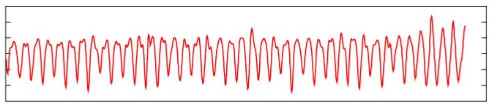
Privacy Issues. When cameras are installed in public spaces, the problem of invasion of privacy is inevitably raised. Since LRFs do not observe the face or any other information that identifies pedestrians, this issue is irrelevant to our method.

The Effect of the Pose of Acceleration Sensor. In this experiments, we attached wearable acceleration sensors to the waist of pedestrians. By computing vertical component of the acceleration, the pose of the sensors does not affect our method. However, acceleration signals differ depending on the position the sensor is attached.

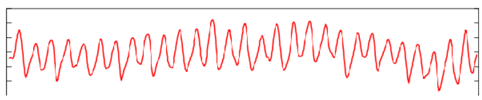
We confirmed the differences that may arise when sensors are carried in different ways: in a pocket, in hands, in a bag (Figure 11). The shape of the observed acceleration signal are not completely same, but the detected peaks of acceleration are still clear and there are no significant difference in computing correlation process.

6 CONCLUSIONS

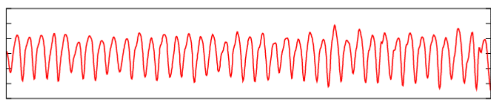
In this paper, to estimate both positions and IDs of pedestrians, we propose a method that associates precise position information using sensors in the environment and reliable ID information using wearable sensors. Since the tracking results of biped feet of a pedestrian and the body oscillation of the same pedestrian correlate, we associate these signals from same pedestrian that maximizes correlation between them.



a) Acceleration signal when a sensor is in a jacket pocket



b) Acceleration signal when a sensor is carried in hands (note that the walking speed becomes slower)



c) Acceleration signal when a sensor is in a bag

Figure 11: Examples of acceleration signals in different carrying conditions.

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 accelerometers, we believe that our method is realistic and can provide a fundamental means of location services in public places.

In future, we'd like to investigate our method when pedestrians carry cellular phones in various way, and when the number of cellular phones is larger. Since we can observe much motions information of pedestrian from accelerometer, we'd like to apply our method to understand natural pedestrian behavior.

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