Indoor Localization utilizing Tracking Scanners and Motion Sensors

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Abstract—In this paper, we propose a new method of highly-accurate mobile phone tracking using infrastructure-based laser-tracking sensors called laser-range scanners (LRS) and pedestrian DR (PDR) on the mobile phones. Each mobile phone continuously obtains readings from accelerometers and gyro sensors to detect moving distance and direction change (PDR information), while the phone user is accurately tracked anonymously by LRS from the infrastructure. Such PDR information, which forms a partial, relative trajectory in each time window, is sent to the infrastructure, and our system finds the best matched one in the set of anonymous (but accurate) laser-based trajectories with absolute coordinates. Then the matched trajectory is given to the identified mobile phone user so that he/she can utilize it as his/her accurate trajectory on the phone. PDR itself is likely to accumulate errors but by the support of LRS, such errors are eliminated in the laser-enabled region (e.g. a circle with a 30m radius by a single LRS). Even in the rest of the region, PDR may continue self-tracking, and such mutual complement works fine for phone tracking in the whole space. We have deployed 6 laser-range scanners and our PDR app on Android smartphones and conducted experiments. As a result, in almost all the cases the method could identify mobile phone users in laser-based trajectories.

I. INTRODUCTION

Rapid progress of sensor device technologies enables to capture human mobility in a variety of locations and situations, and such a trend promotes many social systems to shift more to be human-centric. For example, accurate location information of visitors or occupants in exhibition events, commercial complex or in office buildings can be utilized in a variety of innovative services such as crowd control for smooth and intelligent navigation and smart building systems. The most popular global system for positioning mobile terminals is GPS, but of course it does not work indoors or in underground. For indoor positioning, WiFi fingerprinting, RFID tags or self-contained systems like pedestrian dead reckoning (PDR) have been well-studied, but those technologies have a certain limitation on accuracy.

Accurate positioning of mobile terminals is very beneficial for navigated users. In particular, in an indoor event space like a trade show, visitors can know booths in front of or behind them, can tweet what they feel with pinpoint location information (like automatic checking-in a location in SNS, which has manually been done by users) and can get recommendation of nearby booths to visit. Our research group has been using object detection devices called laser-range scanners, which are often used for security (intruder detection), or autonomous cars recently. Each LRS can cover a wide region (e.g. a circle with a 30m radius) and detect the presence and movement of objects there with only centimeter order errors. Using such devices for mobile phone tracking is a promising approach in terms of accuracy, but the problem is how we identify a particular mobile phone user in the set of anonymous pedestrian tracking information. To cope with this problem, in our previous work [1], each mobile phone collects proximity information with other mobile phones by short-range wireless communication such as Bluetooth, and the location with the most similar proximity information is found in the set of laser-tracked, anonymous but accurate positions. If it is the correct matching, then the location of the user can be identified with very small error, and it can be fed-back to the user as his/her pinpoint location.

Here our goal is to deploy such a highly-accurate, laser-supported mobile node positioning mechanism in more public open space like office buildings and trade shows. In this viewpoint, our previous work [1] assumes high user density in the closed space such as a party space, and thus does not fulfill the requirement. Then it is required to utilize a self-contained positioning mechanism that works with the laser-based tracking to achieve more usable and highly-accurate positioning.

In this paper, we propose a method of mobile node positioning using laser-range scanners (LRS) and pedestrian dead reckoning (PDR). Each mobile phone continuously obtains readings from accelerometers and gyro sensors to detect moving distance and direction change (PDR information), while the phone user is accurately tracked anonymously by LRS from the infrastructure. In particular, we apply the stride estimation algorithm of [2] based on Z-axis amplitude, and normal step estimation using peak intervals in PDR. Such PDR information, which forms a partial, relative trajectory in each time window, is sent to the infrastructure, and our system finds the best-matched one in the set of anonymous (but accurate) laser-based trajectories with absolute coordinates. Then the matched trajectory is given to the identified mobile phone user so that he/she can utilize it as his/her accurate trajectory on the phone. PDR itself is likely to accumulate errors but by the support of LRS, such errors are eliminated in the laser-enabled region (e.g. a circle with a 30m radius by a single LRS). Even in the rest of the region, PDR may continue self-tracking, and such mutual complement works fine for phone tracking in the whole space.

We have conducted experiments on a whole floor of our school building based on scenarios that cover a variety of mobility patterns of pedestrians. We have deployed 6 laser-range scanners and our PDR app on Android smartphones. As a result, in almost all the cases the method could identify
mobile phone users in laser-based trajectories.

II. RELATED WORK

A. Indoor Localization Technology for Mobile Devices

Considerable research effort has been made towards accurate indoor positioning of mobile devices. The most basic, but robust approach is anchor-based systems; a number of anchor devices are installed at known locations, so that a mobile device can estimate its own position by measuring distances to those anchors using radio, infra-red or audio signals. Positioning accuracy basically depends on the type of signals for the distance measurement. Ultra-wideband (UWB) radio is a promising technology to obtain fine distance resolution in indoor environments since it can eliminate impact of multipath signals on measurement accuracy by precisely detecting the signal reception time. UbiSense [3] is an example of such UWB-based positioning systems. Some other systems like ActiveBat [4] and Cricket [5] employ ultrasound signals to achieve sub-meter position granularity. However, most of these systems basically require line-of-sight communication between the anchors and mobile devices. Consequently, a huge number of anchors are needed to achieve reasonable accuracy, which makes them infeasible for large-scale deployment (e.g., to cover a large complex commercial building).

As an alternative solution, pedestrian dead reckoning (PDR) technology has been well investigated so far. PDR roughly estimates trajectory of a pedestrian using inertial sensors [6]–[9]. While most of existing PDR algorithms assume that sensors are tightly attached to a certain part of the human body, some recent work mitigates this constraint and achieves reasonable trajectory estimation accuracy using off-the-shelf mobile devices (e.g., smartphones). To cope with large position errors due to sensor noise and unexpected motion of the devices, Refs. [6], [8], [9] employ map-matching based on particle filtering. More recent work like PCN [10] and collaborative PDR [11] reports that positioning accuracy can be improved by local collaboration among neighboring users. Although these error correction mechanisms have been proved effective, it is still hard to achieve high positioning accuracy that is comparable to the anchor-based positioning systems. Our system is relevant to the PDR technology since we also detect motion of phone holders using accelerometers and gyro sensors in mobile devices. While it may also be possible to perform trajectory identification by directly comparing the PDR-based trajectories with those from LRS-based tracking systems, large errors in the PDR-based trajectories would significantly affect the identification accuracy. We effectively enhance robustness against sensor noise and other environmental factors by utilizing traveled distance and changes in walking direction, both of which can be detected with sufficient reliability by built-in sensors of commercial mobile devices.

B. Crowd Tracking using Laser Range Scanners

Laser range scanners (LRSs) have been recently attracting significant attention as an enabler of accurate crowd tracking and crowd behavior detection. LRSs can precisely measure the distance to surrounding objects with eye-safe laser pulses, and can cover tens of meters with each sensor. A canonical approach to LRS-based crowd tracking is to place the sensors at the height of pedestrians’ waist and horizontally scan the field with laser pulses. By calculating the difference between the current measurement and the background information (e.g., walls and still objects), the system can accurately detect location of the pedestrians [1], [12]. In order to mitigate the occlusion problem (i.e., some pedestrians may not be detected since the laser pulses are often blocked by other persons or obstacles), Ref. [13] propose to place the sensors at the height of the ankles.

The information provided by the LRS-based tracking systems is only presence and location of the pedestrians. Thus they cannot identify correspondence between the locations and mobile phones, which is necessary for mobile-phone-based location services.

C. Trajectory Identification

As discussed above, trajectory identification is an important task for utilizing the precise location information from crowd tracking systems for a variety of personal location services on mobile devices (e.g., pedestrian navigation). Ref. [14] proposes a solution in this direction using wearable RFID tags. LRSs continuously track locations of pedestrians, and then the detected trajectories are associated with each tag when the tag holders pass by RFID readers in the environment. Since a number of RFID readers are needed to improve accuracy of trajectory identification, it would not be suitable for pedestrian tracking in a large area. We have recently proposed a trajectory identification mechanism based on short-range wireless communication (e.g., via Bluetooth) among neighboring mobile phones [1]. It detects proximity between the phones using the communication logs and calculates consistency between the communication-based proximity information and the location data from a LRS-based tracking system to find correspondence between the trajectories and phones. This work basically assumes that a sufficient number of phone holders are continuously walking around the target area, where LRSs can scan almost the entire region. The identification accuracy is likely to degrade when the number of pedestrians is extremely low, since the phones can hardly collect a sufficient amount of proximity features in such a situation. Ref. [15] detects motions of phone holders using accelerometers and gyro sensors in their mobile phones, and matches them with the trajectories from a vision-based pedestrian tracking system. It employs binary motion state (i.e., walking or stopping) and changes in walking direction as feature values for trajectory identification. In crowded situations, it may often happen that multiple phone holders have similar feature values, making it difficult to uniquely identify the correspondence between the trajectories and phones.

D. Our Contribution

In this paper, we propose a novel approach that robustly and accurately estimates locations of each mobile phone user by fusion of crowd trajectory information from LRSs and motion-based features from accelerometers and gyro sensors in mobile phones. Since it employs only built-in sensors in off-the-shelf mobile devices, we do not need any additional infrastructure for trajectory identification as in Ref. [14]. In addition, the motion-based features can be collected independently at each mobile device. Thus, in contrast to the previous work in Ref. [1], the trajectory identification accuracy does not degrade even if the density of phone holders is extremely low. The work in
Ref. [15] is the most relevant to our work in the sense that it also captures motion of pedestrians using inertial sensors in mobile devices. While it utilizes only binary motion state and changes in walking direction as feature values for trajectory identification, our system also detects traveled distance of each phone holder and use it for identification to effectively enhance robustness against higher pedestrian density.

III. OVERVIEW

Fig. 1 shows the architecture of the proposed system. We assume that several LRSs are deployed in the target area. These LRSs scan objects in the area, and measure distances from the sensors to the objects. Their measurements are transmitted to the server periodically. The server analyzes the data, and estimates the positions and the trajectories of pedestrians in the area. In addition, in our proposed system, we also suppose that several pedestrians have mobile terminals with an accelerometer and a gyroscope. The mobile terminal estimates the moving distance and direction for each pedestrian from the data obtained by these two sensors. These data are further transmitted to the server. At last, in order to match between the trajectories derived from LRSs and the moving distance and direction derived from motion sensors, the proposed method finds an appropriate trajectory for each pedestrian who has a mobile terminal. Thus, the proposed system can give these pedestrians the highly-accurate positions and trajectories, which enables new intelligent navigation and building systems. We explain the position and trajectory estimation with LRSs, and the moving distance and direction estimation with motion sensors in the following subsections. We also show the matching algorithm between these data in Section IV.

A. Trajectory Estimation by using LRSs

We assume that several LRSs are placed at the waist level height in the target area so that we can track pedestrians in the field continually. Since each LRS measures 1080 points within a 270 degree angle ranges with 25 ms interval, a pedestrian can be detected as several points near by each other as shown in Fig. 2. The outline can be formed from the detected points according to Ward’s method, which is one of clustering algorithms. In addition, the centroid of the pedestrian can be derived from the outline in the following steps. As shown in the figure, the line can be constructed between the two edge points to the LRS from the outline. We can also obtain the perpendicular to the line. Thus, the point, whose distance to the nearest detected point is the radius of the outline, on the perpendicular can be the centroid of the pedestrian. Finally, the proposed method derives a trajectory for a pedestrian by connecting the centroids over time. Since LRSs scan the points with 25 ms interval and the distances between centroids are very small, we can connect the centroids whose distance is smaller than a threshold. If we find new centroid, we create new pedestrian in the area.

B. Moving Distance and Direction Estimation with Motion Sensors

For the pedestrian having a mobile terminal, the proposed method also estimates the moving distance and direction using the accelerometer and gyroscope attached to it. While a pedestrian is walking, we can see fluctuations in vertical accelerations. Thus, the proposed method detects walking steps for each pedestrian base on this observation. Moreover, we can estimate the moving distance for a pedestrian from the number of steps and the distances for walking steps.

1) Distance Estimation: The dash line in Fig. 3 shows vertical accelerations over time while a pedestrian is walking. As shown in the figure, we can see a periodic pattern according to a step, but we can see also several different types of noises. Thus, we use a low pass-filter for the measurements to eliminate such noises. We describe the measurement value from the accelerometer and the filtered value as $x_i$ and $X_i$, respectively. The relationship between them is represented in the following equation, where $w$ is a weight value for a current measurement and previous filtered data.

$$X_i = \begin{cases} w x_i + (1-w)X_{i-1} & \text{if } i > 0 \\ w x_0 & \text{if } i = 0 \end{cases}$$ (1)

The line in Fig. 3 shows the vertical accelerations after filtering. Since the noises were removed as shown in the figure, we can see the fluctuation caused by walking steps more clearly. After this process, the proposed method can detect a step from the local maximum and minimum values in the filtered data. In addition, according to Ref [2], the moving distance for each step can be calculated by the following equation where a local maximum value and local minimum value are denoted as $a_{max}$ and $a_{min}$, respectively.

$$l = k \cdot \sqrt{a_{max} - a_{min} + \alpha}$$ (2)

For each step detection, the proposed method estimates a distance for a step and calculates the total distance by adding these distances.
2) Moving Direction Estimation: We also estimate the moving direction by using motion sensors. We calculate the variation of the moving direction $\Delta \theta_i(t', t)$ between time $t'$ ($< t$) and time $t$ in the following equation where the angular velocity from a gyroscope at time $t$ is denoted as $\omega(t)$.

$$\Delta \theta_i(t', t) = \int_{t'}^t \omega(t) \, dt \quad (3)$$

For each step detection, we can also derive the variation of the moving direction based on the equation.

3) Accuracy of distance/direction estimation: In order to know the accuracy of distance/direction estimation we have conducted the following preliminary experiments: Five participants walk on a 40m-long straight path 10 times at three different velocities, holding an Android smartphone. A sensing application is run on the phone to record acceleration readings during the walking motion. We applied the step detection algorithm to these acceleration data, and calculated the average step length by dividing the total walking distance (i.e., 40m) by the number of steps. Based on the experimental result, we have obtained the parameter in Eq. 2 for each participants.

The error distribution of the step length estimation is shown in Fig. 4. The figure also shows a Gaussian distribution obtained by linear regression. As seen, the errors in step length estimation follow the normal distribution whose mean and standard deviation are 0.01 [m] and 0.13 [m], respectively.

We have also conducted an experiment to evaluate the errors in moving direction estimation. In this experiment, 6 participants walk in one direction for 5 steps and then change their moving direction by -15, -30, -45, -60, -75, -90, 15, 30, 45, 60, 75 or 90 degrees. We conducted 20 experiments for each angle. The distribution of the estimation error is shown in Fig. 5. We also show a Gaussian distribution obtained by linear regression in the same figure. As seen, the direction estimation errors also follow a Gaussian distribution whose mean and standard deviation are 0.04 [rad] (2.3°) and 0.18 [rad] (10°), respectively. From these results, we can see that our method can derive moving distances and directions in sufficient accuracy.

IV. Matching Algorithm

At time $t$, we denote a set of pedestrian trajectories obtained from LRSs as $U(t)$. It is composed of pedestrian positions represented as $u_i = \langle p_i^{1}, ..., p_i^{n} \rangle$, where $n \tau$ is the first time $u_i \in U(t)$ was measured by the LRSs. In the proposed method, by estimating moving distance and directions from smartphones, and then matching them with the LRS-based trajectories $u_i \in U(t)$, we find an appropriate LRS-based trajectory corresponding to each mobile phone. We denote the time when $k$ th step is detected by a mobile phone, the moving distance in $k$ th step and the moving direction from $k-1$ th step to $k$ th step as $t_k, l_k$ and $\Delta \theta_k$ can be estimated from an accelerometer and a gyroscope in a mobile phone by Eq. 2 and 3, respectively.

LRSs can derive high-accurate trajectories while motion sensors can derive rough trajectories composed of moving distances and directions. Therefore, it is not easy to match them based on their geometry shapes. Since both LRSs and motion sensors can know that pedestrians do not move in the area, the proposed method finds correspondences between the mobile phones and the LRS-based trajectories in two processes matching them based on stop and go information in addition to the geographical information. If we know that a pedestrian who has a mobile phone is not moving at time $t$, we can remove the LRS-based trajectories whose pedestrian is moving at $t$ from the candidates. After that, we calculate the similarity of moving distances and directions in the candidates, and derive an appropriate trajectory. In the following subsections in this section, we explain the two processes in detail.

A. Filtering based on Stop and Go Information

If $\Delta t_k = t_k - t_{k-1}$ exceeds a threshold $T$, we define this period as a static period since a pedestrian does not move in a certain time. In the proposed method, we filter LRS-based trajectories contained in $U(t)$ on the basis of total moving distance of pedestrian trajectories $u_i \in U(t)$ at each static period $\{(t_{k-1}, t_k) | t_k - t_{k-1} > T\}$. A total moving distance of $u_i$ at a static period $(t_{k-1}, t_k)$ is defined by Eq. 4.

$$d_i(t_{k-1}, t_k) = \sum_{s = \lfloor (t_{k-1}) / \tau \rfloor}^{\lfloor (t_k - t_{k-1}) / \tau \rfloor} ||p_i^{t-s\tau} - p_i^{t-(s+1)\tau}|| \quad (4)$$

If there is a period whose $d_i(t_{k-1}, t_k)$ exceeds 0.5 meters after $u_i \in U(t)$ is detected, $u_i$ is excluded from the candidates of pedestrian trajectories corresponding to the pedestrians.
B. Matching Likelihood

Let \( U(t) \subseteq U(t) \) be a subset after \( U(t) \) was filtered. In the proposed method, we define the likelihood (matching likelihood) how similar a trajectory \( u_i \in U(t) \) is to the moving distances and directions for a pedestrian who has a mobile phone. As shown in the previous section, the estimation error in the moving distances follows the normal distribution \( \mathcal{N}(\mu_i, \sigma_i^2) \) \((\mu_i = 0.01[m], \sigma_i = 0.13[m])\). Thus, the total distance for five steps can be calculated by \( l_{k, k-4} = l_k + l_{k-1} + \cdots + l_{k-4} \).

The probability of the estimation error can be represented in the following equation, which is equivalent to \( \mathcal{N}(5\mu_i, 5\sigma_i^2) \).

\[
L(l) = \frac{1}{\sqrt{10\pi\sigma_i^2}} \exp \left\{ -\frac{(l - 5\mu_i)^2}{10\sigma_i^2} \right\}
\]

On the other hand, the total distance for five steps \( \tilde{l}_{k, k-4} \) obtained by LRSs can be represented in the following equation.

\[
\tilde{l}_{k, k-4} = \sum_{k' = k-4}^k ||p(t - [t - t_k'])/\tau) - p(t - [t - t_{k-1}]'/\tau)||
\]  

(5)

Since \( \tilde{l}_{k, k-4} \) is calculated from LRSs and the LRSs can track pedestrians with small errors (ex. the measurement errors of UTM-30LX [16] are at most 50mm.), the trajectories from LRSs show the exact trajectories for pedestrians. Therefore, the likelihood \( L_{i}^{dist}(l_{k, k-4}) \) can be provided by Eq. 6.

\[
L_{i}^{dist}(l_{k, k-4}) = L(l_{k, k-4} - \tilde{l}_{k, k-4})
\]  

(6)

\( \tilde{l}_{k, k-4} \) is calculated every time a new step is detected on a mobile phone. We define the mean of the likelihoods to all step as a matching likelihood \( L_{i}^{dist} \) for \( u_i \).

\[
L_{i}^{dist} = \frac{\sum_{t > t_{n-\tau}} L_{i}^{dist}(l_{k', k-4})}{k - k_{min} + 1}
\]  

(7)

\( k \) is the current step and \( k_{min} \) is the first step after the appearance of \( u_i \) in the equation.

Next, we consider the likelihood based on the variation of the moving direction. This variation in five steps \( \Delta \theta_{k, k-4} \) based on measured data from a gyroscope follows the normal distribution \( \mathcal{N}(\mu_\theta, \sigma_\theta^2) \) \((\mu_\theta = 0.04[rad], \sigma_\theta = 0.18[rad])\) from the result in Section III-B3. The variation of the moving directions with LRSs can be calculated by the following equation.

\[
\Delta \theta_{k, k-4} = \arg(p_{t - [(t - t_{k})/\tau])} - p_{t - [(t - t_{k+0.5})/\tau])} - \arg(p_{t - [(t - t_{k-0.5})/\tau])} - p_{t - [(t - t_{k-4})/\tau])}
\]  

(8)

At the current step \( k \) and step \( k - 4 \), we calculate the moving directions comparing the position at the time and the position before 0.5 seconds. Thus, the variation of the moving direction is derived by subtracting the direction at the current step from the direction at the step \( k - 4 \).

By using the estimate error model based on measured values from a gyroscope, we can also define the likelihood to \( \Delta \theta_{k, k-4} \) as shown in Eq. 9.

\[
L_{i}^{dir}(\Delta \theta_{k, k-4}) = \frac{1}{\sqrt{2\pi\sigma_\theta}} \exp \left\{ -\frac{((\Delta \theta_{k, k-4} - \Delta \theta_{k, k-4} - \mu_\theta)^2}{2\sigma_\theta^2} \right\}
\]  

(9)

We calculate the likelihood by Eq. 9 in all step that \( \Delta \theta_{k, k-4} \) exceeds a threshold \( \Theta \). Thus, we define a mean of the likelihood \( L_{i}^{dir} \) as the likelihood based on the variation of the moving directions for \( u_i \). Furthermore, in this paper, we set \( \Theta = 0.07[rad] \) on the basis of the result in Section III-B3.

\[
L_{i}^{dir} = \frac{\sum_{t > t_{n-\tau}} \delta(\Delta \theta_{k', k-4})L_{i}^{dir}(\Delta \theta_{k', k-4})}{\sum_{t > t_{n-\tau}} \delta(\Delta \theta_{k', k-4})}
\]  

(10)

\( \delta(\Delta \theta_{k', k-4}) \) derives 1 if \( \Delta \theta_{k', k-4} > \Theta \), otherwise 0. The matching likelihood \( L_i \) of trajectory \( u_i \) is defined as product of a distance-based likelihood and a direction-based likelihood.

\[
L_i = L_i^{dist} \cdot L_i^{dir}
\]  

(11)

Therefore, we calculate a matching likelihood \( L_i \) for all \( u_i \) included in \( U(t) \), and regard a trajectory whose likelihood is the largest as a trajectory corresponding to a mobile phone user.

V. EVALUATION

A. Methodology

In order to evaluate performance of the proposed method, we conducted an experiment using LRSs (UTM-30LX [16]) and Android smartphones (Nexus S). In this experiment, we put LRSs at six locations that are indicated by circles in Figure 6. One subject walked in the field along five paths shown in Figure 7 at three levels of speed, namely, 0.6[m/s] (slow-speed), 1.1[m/s] (medium-speed) and 1.6[m/s] (high-speed). During the experiment, he held an Android smartphone in front of his body. Our sensing application was running on the phone, and it continuously calculated and recorded the feature values in Section III-B based on accelerometer and gyroscope readings. The subject starts the application when he enters the monitored area by the LRSs. At the same time, we tracked his trajectories based on the measurement data from LRSs using the algorithm in Section III-A.

By aligning start time of the 15 experiments by adding offsets to the timestamps of the mobile-phone-based feature values and the LRS-based trajectories, we virtually created a data set, in which 15 pedestrians walk in the field at the same time. We applied our matching algorithm in Section IV to the data set above, and examined the characteristics of the matching likelihood.
B. Results

1) Difference in the walking paths: First, we examined how difference in walking paths affects the matching likelihood. For each of the 15 mobile phones, we calculated the matching likelihood with 5 LRS-based trajectories that have the same walking speed and different paths, and compare them in Figure 8. The solid lines in the figure represent the matching likelihood with the corresponding LRS-based trajectory, while the dotted red lines indicate the time when the mobile phone user passed through the locations where the five users start to walk toward different directions (indicated by a dotted circle in the Figure 7).

Once they start walking toward different directions, matching likelihood with the wrong trajectories steeply declines and the likelihood with the corresponding trajectory becomes the largest in almost all cases (see Figure 8 (j) for example). Thus we can confirm that the change in walking direction is an appropriate feature value for the trajectory identification.

2) Difference in the walking speed: We also examined how difference in walking speed affects matching likelihood. For each of the 15 mobile phones, we calculated the matching likelihood with 3 LRS-based trajectories that have different walking speed (i.e., slow, medium and high speed) and the same path, and compare them in Figure 9.

In all cases, the matching likelihood with the corresponding LRS-based trajectory takes a much larger value than that with the other trajectories. The likelihood with the wrong trajectories is almost zero in most cases, meaning that the walking speed information effectively contributes to narrow down the solution space.

VI. Conclusion

In this paper, we have presented a method to find correspondence between mobile phone users and crowd trajectories from LRSSs based on measurement data from built-in sensors in off-the-shelf smartphones. We detected traveled distance and changes in walking direction using accelerometer and gyroscope readings, and then identified a corresponding trajectory for each user based on consistency of these features. Through experiments using real LRSs and Android smartphones, it has been confirmed that the proposed method can identify the trajectories of each mobile phone user from a set of LRS-based trajectories with high accuracy.

As future work, we plan to improve robustness against higher pedestrian density. Frequency of occlusion is likely to be much higher in extremely crowded situations like busy railway stations. Consequently, the LRS-based trajectories would be frequently disconnected, confusing the trajectory identification task. In addition, it may often happen in crowded areas that multiple pedestrians walk in a similar manner. In this case, their feature values also become similar to each other and thus it may become difficult to uniquely identify the corresponding trajectory. Combination with WiFi fingerprinting technology would be a possible solution to cope with these problems. Moreover, we will analyze performance of our method under various situations by extensive simulations and field experiments.

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Fig. 8. The result of calculating matching likelihood on a variety of walking paths.
Fig. 9. The result of calculating matching likelihood on a variety of moving speeds.