SparseTrack: Enhancing Indoor Pedestrian Tracking with Sparse Infrastructure Support

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***Abstract*—Accurate indoor pedestrian tracking has wide applications in the healthcare, retail, and entertainment industries. However, existing approaches to indoor tracking have various limitations. For example, location-fingerprinting approaches are labor-intensive and vulnerable to environmental changes. Trilateration approaches require at least three Line-of-Sight (LoS) beacons to cover any point in the service area, which results in heavy infrastructure cost. Dead Reckoning (DR) approaches rely on knowledge of the initial user location and suffer from tracking error accumulation. Despite this, we adopt DR for location tracking because of the recent emergence of affordable hand-held devices equipped with low cost DR-enabling sensors. In this paper, we propose an indoor pedestrian tracking system which comprises a DR sub-system implemented on a mobile phone, and a ranging sub-system with a sparse infrastructure. A probabilistic fusion scheme is applied to bound the accumulated tracking error of DR when new range measurements are available from sparsely deployed beacons. Experimental results show that the proposed system is able to track users much better than DR alone, with reductions in average error by up to 71.9%. The system is robust and works well even when the initial user location is not available and range updates are intermittent. This highlights the potential of using sparse but reasonably accurate partial information to limit location tracking errors.**

***Index Terms*—Pedestrian tracking, sensor fusion.**

I. Introduction

Accurate indoor pedestrian tracking has wide applications in the healthcare, retail, and entertainment industries. Well-known services such as the Global Positioning System (GPS) are normally unavailable indoors. Therefore, solutions to the indoor tracking problem have to be built on top of other technologies and infrastructure inside the building. Fingerprinting, trilateration, and dead reckoning (DR) are the main approaches to achieve location accuracy finer than room level.

While delivering satisfactory localization accuracy, fingerprinting approaches [1] require high manpower cost for location fingerprint collection. Moreover, this approach is vulnerable to environmental changes.

On the other hand, a typical trilateration system requires the coverage of at least three Line-of-Sight (LoS) ranging beacon nodes (BNs) at any point in the service area [2]. Technologies with high ranging accuracy, such as Ultra-Wide-Band (UWB) and ultrasound, are limited in coverage distance in order to save power and limit interference. Therefore, a large number of BNs are needed to provide tracking services over a large indoor area, incurring high infrastructure cost.

The DR approach has been widely adopted for real-time indoor pedestrian location tracking. A typical pedestrian DR system relies on sensors, such as accelerometers and magnetometers, to estimate relative displacement, starting with the known initial user location. Each location update is accomplished by adding the current estimated displacement to the previously estimated location. Since the estimates are based on noisy sensors, the error of a DR system can accumulate over time, regardless of whether the displacement is computed by directly double integrating the acceleration measurements [3], or by detecting the user's steps [4].

Recently, hand-held devices (e.g., Apple iPhone 3GS and HTC G1) equipped with accelerometers and magnetometers have become commercially accessible. The fact that more and more people will have DR-enabling sensors on their hand-held devices has created new opportunities in the realization of a cost-effective location tracking system. From a user's perspective, using pedestrian navigation services implemented on affordable hand-held devices is also more economical and user-friendly, compared to mounting dedicated sensors on their legs or waists. For these reasons, we focus on the design and implementation of a DR-based indoor pedestrian location tracking system using readily available mobile devices equipped with an accelerometer and a digital compass.

However, the quality of the sensor measurements on such devices may be limited due to the cost constraints of mass market products. In a DR system, the severity of this issue is further magnified by the cumulative nature of the tracking error. We address this problem by incorporating a sparse ranging sub-system which provides partial location side information that can be used to bound the cumulative DR tracking error.

A. The Value of Sparse and Partial Information

Various schemes have been proposed in an effort to correct the tracking error of a DR system. A commonly adopted approach is to utilize complete location information, such as GPS coordinates, for correction purposes [5], [6], [7].

However, complete location information indoors requires extensive system resources, e.g., dense BNs for trilateration.

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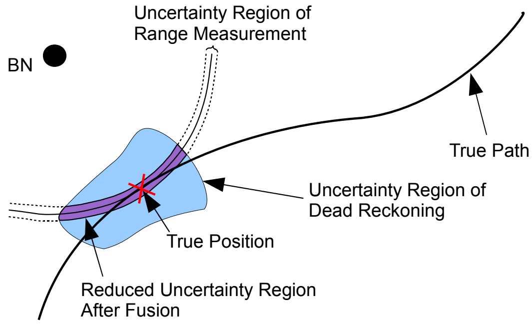


Fig. 1. Snapshot of uncertainty regions at a particular time instance.

As we will see below, engineering tradeoffs suggest using finite system resources to provide sparse and partial location information as side information to the main location tracking system. This forms the motivation for our work, which is to explore the potential value of sparse and partial side information to improve location tracking accuracy.

Suppose we have a DR-based indoor pedestrian tracking system in place and we would like to deploy an infrastructure to provide side information to improve location tracking. In this context, there is a tension between several factors: having a finite set of resources; meeting coverage specifications; and satisfying accuracy requirements. One design choice is to use the limited infrastructure resources to provide reliable and complete location information (e.g., using trilateration) for a small fraction of the service area. However, in indoor environments such as museums, shopping malls, and campus buildings, users are constantly moving over a large service area. A better design tradeoff may be to deploy the limited infrastructure resources to provide partial but reasonably reliable location information over a larger service area in a sparse and intermittent manner. The intuition is that, although partial information such as the range from a single BN is ambiguous for location purposes on its own, it can be used as side information to reduce the uncertainty region for another location tracking system. This point can be illustrated in Fig. 1. The light shaded area is a snapshot of the uncertainty region of a mobile user being tracked by a DR system. The ringed area between the dotted lines is the uncertainty region of a sparse ranging system, which can lead to a large location uncertainty on its own. However, it can be used to significantly reduce location tracking error by considering its intersection with the DR uncertainty region. The reduced uncertainty region is represented by the dark shaded area.

B. Contributions of Our Paper

In this paper, we propose SparseTrack, an indoor pedestrian tracking system which consists of a DR sub-system and a ranging sub-system with a sparse infrastructure. The DR sub-system is the combination of a digital step counter and a digital compass, implemented using sensors on a mobile phone. The ranging sub-system is deployed in such a way that, at any point within the service area, *at most one* LoS ranging BN can be heard. The DR sub-system provides real-time user displacement estimation but has cumulative error. Occasionally, when a range measurement from one infrastructure BN is heard, it can be used to constrain and correct the accumulated tracking error. We propose a Maximum Likelihood (ML) sensor fusion scheme to correct the tracking error for the general case in which the accuracy and resolution of the ranging sub-system may vary. A prototype of the proposed scheme is implemented for experimental verification with sensors on a hand-held device and a reliable ranging system. As will be shown in Section V, SparseTrack is able to provide better tracking performance compared to a DR system, regardless of whether the knowledge of the initial user location is available or not. Moreover, even when the range corrections are very sparse both temporally and spatially, our proposed system still delivers fairly accurate tracking performance. We find that the proposed system reduces the average tracking error by 27.1% to 71.9%, compared to DR alone. In addition, implementation of the proposed method does not require the accessibility of the map information.

The rest of the paper is organized as follows. Section II summarizes the works in the literature on pedestrian tracking with various approaches. Section III describes the working mechanisms and issues of the sensors that we employ in our proposed system. In Section IV, we first propose a generalized probabilistic sensor fusion scheme for user tracking, and then consider the special case in which reliable range sensors are used. Section V presents experimental results, including sensor evaluations, tracking algorithm performance, and discussion. Finally, we conclude our work in Section VI.

II. Related Work

We classify the tracking methods in the literature into three major categories, namely, location sampling (LS), DR, and hybrid schemes, which utilize external technology to correct the DR tracking error.

A. Location Sampling

In a LS tracking system, successive location estimations are sampled on the user trajectory using popular methods such as fingerprinting and trilateration.

The fingerprinting approach requires location-dependent signal parameters to be collected at a few "training locations" as "fingerprints" during an off-line phase [1], [8]. During the online phase, signal parameter values collected from the target device with unknown location can be compared with the fingerprints for location inference. The intensive labor input during the off-line phase is a major drawback of this approach. Moreover, fingerprinting systems are vulnerable to environmental changes due to the changes of room layout, and the real-time movement of the crowd.

On the other hand, most practically implemented trilateration systems rely on accurate range measurements from at least three LoS infrastructure BNs with known locations. However, RF-based fine resolution range measurements require high system sampling rate [2], [9], [10], which limits the transmission power and working distance of a BN in order to save power and limit interference. Ultrasound-based range measurement in the Cricket localization system [11] is also limited in working distance for power control purpose. In an indoor environment, LoS condition is often broken by the heavy presence of physical barriers. Therefore, a large number of BNs are required in order to provide trilateration coverage with good accuracy in a large indoor service area, which incurs high cost in the infrastructure.

B. Dead Reckoning

Implemented using on-device sensors, such as accelerometer and digital compass, DR systems are not only less dependent on the infrastructure, but also less affected by the environmental changes. The DR approach estimates the current user location by adding estimated displacement to the previous location estimation [12]. Some early efforts in DR estimate the displacement by double integrating the acceleration over time, which suffers from rapid error accumulation [13]. Kalman filter [14], zero-velocity-update theory [15], and spectrum control [16] techniques have been proposed to reduce the cumulative error. In [3] and [12], DR systems which comprise digital step counter and digital compass have been proposed. Heavy calibrations are required in [12] for satisfactory tracking performance. Robust step counter implementation relying on two-axis acceleration measurement is proposed in [4].

C. Hybrid Schemes

In the domain of outdoor tracking, hybrid schemes are proposed in order to reduce the cumulative DR tracking error with the aid of external technologies. Many works in this category use the GPS device's output as a complete piece of location information for the correction [5], [6], [7]. A correction scheme using range information is proposed in [17] for outdoor on-wheel robotics tracking. The DR is accomplished with fine accuracy wheel encoder (with 0.001 m/meter standard deviation) and gyroscope, which is not applicable for tracking walking human. Tracking errors are frequently corrected using range measurements that arrive at an average rate of 7 times/s. Range BNs are deployed such that 2 or more of them can be heard at any point of the robot's path.

III. SENSOR DESCRIPTION

In order to verify the performance of the proposed tracking algorithm, we have chosen to use the accelerometer and the digital compass in the HTC G1 phone for the implementation of the digital step counter and the step orientation estimation respectively. For the realization of the range sensor and the infrastructure BNs, we have chosen to use the Cricket Motes. Before proceeding to the details of the proposed scheme, it is necessary to introduce the working mechanisms and some implementation issues of the three sensors, namely, the digital step counter, the digital compass, and the range sensor.

A. Digital Step Counter

Like most works in the literature, we implement the digital step counter based on the accelerometer's measurements. Instead of utilizing the acceleration readings from only one axis, as was done in [12], we adopt a method which is similar to that of [4], except that we use acceleration measurements from all three axes for more robust step detection.

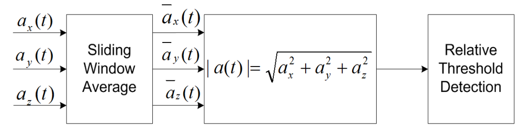


Fig. 2. Block diagram of a simple digital step counter.

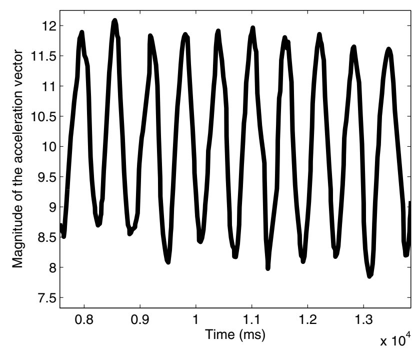


Fig. 3. Typical acceleration variation over time for 10 steps.

As shown in Fig. 2, in order to reduce noise, the three axes' acceleration readings at time instance t, namely, $a_x(t)$, $a_y(t)$, and $a_z(t)$, are first passed to an averaging window containing the readings of the most recent 200 ms, yielding $\bar{a}_x(t)$, $\bar{a}_y(t)$, and $\bar{a}_z(t)$. Next, the magnitude, $|\bar{\mathbf{a}}(t)|$, of the 3-D acceleration vector, $\bar{\mathbf{a}}(t)$, is computed as,

$$|\bar{\mathbf{a}}(t)| = \sqrt{\bar{a}_x^2(t) + \bar{a}_y^2(t) + \bar{a}_z^2(t)}. \tag{1}$$

Fig. 3 shows the temporal variation of $|\bar{\mathbf{a}}(t)|$ for 10 steps taken at normal walking speed. A new step is detected if a valid local maximum and a valid local minimum are detected in sequence. A local maximum is valid if it occurs at least 200 ms after the most recent valid local minimum, and the value of $|\bar{\mathbf{a}}(t)|$ at the local maximum exceeds that of the most recent local minimum by at least a threshold value, $\Delta_{\text{threshold}}$. Similarly, a local minimum is valid if it occurs at least 200 ms after the most recent valid local maximum, and the value of $|\bar{\mathbf{a}}(t)|$ at the local minimum is lower than that of the most recent local maximum by at least $\Delta_{\text{threshold}}$. The choice of the 200 ms time difference threshold is due to the fact that, at normal walking speed, humans approximately take two steps per second, which leads to four peaks correspondingly. Hence, it would be safe to pick 200 ms as the minimum inter-peak time difference. Both the detection threshold $\Delta_{\text{threshold}}$ and the stride length l may vary when different users are carrying the sensors. However, simple calibrations can be performed to estimate these two parameters for a specific user. For example, $\Delta_{\text{threshold}}$ can be determined by asking the user to walk a known number of steps. On the other hand, the stride length l can be determined by counting the number of steps taken for a user to cover a fixed distance.

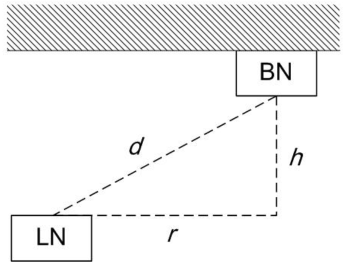


Fig. 4. Original and projected range measurements.

B. Digital Compass

The digital compass in the HTC G1 phone reports orientation readings in three principal axes, namely, yaw, pitch, and roll. Assume that, when a hand-held device is being used, the yaw direction of the device is aligned with the user's heading. Therefore, a simple method to estimate the direction of a step and to reduce the measurement noise is to take the average of the yaw readings between the starting and the ending time of the step. However, in a step taken when the user is turning, the yaw direction of the device will only be aligned with the true step orientation at the end of the step. By considering this fact, we estimate the user's heading by averaging over only the yaw readings collected during the last 200 ms of a step.

C. Range Sensing Infrastructure

The range measurement in a Cricket-based ranging system is carried out between a BN and a listener node (LN). The BN periodically sends out an RF packet and an ultrasound pulse at almost the same time, t_0. Upon receiving the RF packet at time t_{RF}, the LN starts to wait for the arrival of the ultrasound pulse. Upon receiving the ultrasound pulse at time t_{US}, or upon a timeout event, the LN stops waiting and starts to listen for new RF packets.

Due to the huge difference between the speed of RF and ultrasound propagation, the difference between $t_{\text{US}} - t_0$ and $t_{\text{US}} - t_{\text{RF}}$ is almost negligible. Therefore, the LN can treat $t_{\text{US}} - t_{\text{RF}}$ as the propagation time of the ultrasound signal. The LN-BN separation, d, can then be simply computed as,

$$d = v \cdot (t_{\text{US}} - t_{\text{RF}}), \tag{2}$$

where v is the speed of ultrasound in air at room temperature.

In practice, the BNs are normally mounted on ceilings to reduce possible blocking of signals by the human body and furniture. As shown in Fig. 4, there is a height difference, h, between a BN mounted on the ceiling and the LN carried by the user. The distance, r, projected onto the 2-D plane is therefore,

$$r = \sqrt{d^2 - h^2}. \tag{3}$$

For the rest of this paper, unless otherwise stated, the term "range measurement" shall refer to the projected 2-D distance after taking the height difference into consideration.

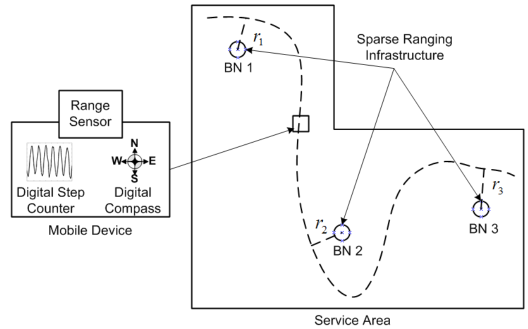


Fig. 5. System architecture of SparseTrack.

IV. Proposed Scheme

A. System Architecture of SparseTrack

In our proposed SparseTrack system as shown in Fig. 5, several ranging BNs are sparsely installed in the service area, functioning as the ranging infrastructure. Since we only require ranging coverage from at most one LoS BN at any point within the service area, the number of BNs is much smaller than that of a typical indoor trilateration system. On the user side, a digital step counter, a digital compass, and a range sensor are integrated into a mobile device to be carried by the user.

The range sensor and the ranging infrastructure form the ranging sub-system. Whenever available, the distance measurement to a nearby BN provided by this sub-system is utilized to correct the accumulated tracking error. More importantly, when a mobile user first appears in the service area, the ranging sub-system is able to constrain the possible initial user locations. The digital step counter and the digital compass form the DR sub-system, which provides the displacement estimation relative to the initial user location, or to the last estimated user location at which a correction was made.

B. Sensor Fusion Algorithm for Correction of Tracking Errors

Although the fine-resolution Cricket ranging system is used to realize SparseTrack for evaluation purposes, in this section, we will first propose a general probabilistic fusion scheme that is applicable to different ranging sub-systems that come with various accuracies and resolutions. We then examine in Section IV-C the special case in which fine-resolution ranging technology, such as the Cricket, is used.

Recall that l is the stride length of a particular user of interest. Let $\bar{l}$ denote the mean of l, and θ_k denote the direction of the k^{th} step event. Therefore, the displacement vector of the k^{th} step is estimated as,

$$\mathbf{s}_k = [\bar{l}\cos\theta_k,\ \bar{l}\sin\theta_k]^T. \tag{4}$$

Let $\mathbf{L}_k = [x_k, y_k]^T$ and $\hat{\mathbf{L}}_k = [\hat{x}_k, \hat{y}_k]^T$ denote the true and DR-estimated user locations after the k^{th} step is detected, respectively. The update for the location estimation purely based on the k^{th} detected step is,

$$\hat{\mathbf{L}}_k = \hat{\mathbf{L}}_{k-1} + \mathbf{s}_k. \tag{5}$$

In a typical scenario, when the m^{th} range measurement, $r_{m,n}$, from the n^{th} BN node located at $[x_n^{\text{B}}, y_n^{\text{B}}]^T$ is available, a correction can be made. In this paper, we propose a

ML scheme for correcting tracking errors. We want to find the location coordinates, $\mathbf{L}_k$, which maximizes the posterior, $f(\mathbf{L}_k|\hat{\mathbf{L}}_k, r_{m,n})$, of the true user location $\mathbf{L}_k$, conditioned on the location $\hat{\mathbf{L}}_k$ estimated by the DR sub-system, as well as the m^{th} range measurement $r_{m,n}$ from the n^{th} BN. From Bayes' Theorem, we have,

$$f(\mathbf{L}_k|\hat{\mathbf{L}}_k, r_{m,n}) = \frac{f(\hat{\mathbf{L}}_k, r_{m,n}|\mathbf{L}_k) \cdot f(\mathbf{L}_k)}{f(\hat{\mathbf{L}}_k, r_{m,n})}. \tag{6}$$

In (6), $f(\mathbf{L}_k)$ can be assumed to be uniform, and $f(\hat{\mathbf{L}}_k, r_{m,n})$ is not affected by the value of $\mathbf{L}_k$. Therefore, the maximization of $f(\mathbf{L}_k|\hat{\mathbf{L}}_k, r_{m,n})$ is equivalent to maximizing the likelihood, $f(\hat{\mathbf{L}}_k, r_{m,n}|\mathbf{L}_k)$.

Due to the facts that the randomness characterized by $f(\hat{\mathbf{L}}_k|\mathbf{L}_k)$ is the result of all previous steps and corrections, and that the randomness characterized by $f(r_{m,n}|\mathbf{L}_k)$ is dependent on the nature of the ranging technology employed, we assume that the two distributions are independent, i.e.,

$$f(\hat{\mathbf{L}}_k, r_{m,n}|\mathbf{L}_k) = f(\hat{\mathbf{L}}_k|\mathbf{L}_k) \cdot f(r_{m,n}|\mathbf{L}_k). \tag{7}$$

The independence assumption here results in simpler computations. More importantly, in some other possible scenarios, when more than one range measurement is available, our proposed scheme can be easily extended by simply multiplying the likelihood functions of all the range measurements together.

In general, the location correction is accomplished by finding the location $\tilde{\mathbf{L}}_k$ that maximizes the product, $f(\hat{\mathbf{L}}_k|\tilde{\mathbf{L}}_k) \cdot f(r_{m,n}|\tilde{\mathbf{L}}_k)$. Numerically, we can compute $f(\hat{\mathbf{L}}_k|\tilde{\mathbf{L}}_k) \cdot f(r_{m,n}|\tilde{\mathbf{L}}_k)$ for a set of discrete points uniformly picked in the service area, and search for the maximum. Gradient Descent based search methods can be applied here to shorten the search time. The correction vector, $\mathbf{c}_m$, that is made possible by the m^{th} range reading, can therefore be expressed as,

$$\mathbf{c}_m = \tilde{\mathbf{L}}_k - \hat{\mathbf{L}}_k. \tag{8}$$

A special yet important case is the first range correction after the user appears in the service area. Before this correction, nothing is known about the user location. Therefore, if the first range measurement, $r_{1,n}$, is made from BN n, the initial user location guess, $\tilde{\mathbf{L}}_0$, should be chosen such that it maximizes $f(r_{1,n}|\tilde{\mathbf{L}}_0)$.

The generalized fusion algorithm is summarized in Algorithm 1. In order to facilitate the computation in practice, the parametric form of both $f(\hat{\mathbf{L}}_k|\mathbf{L}_k)$ and $f(r_{m,n}|\mathbf{L}_k)$ are required. First of all, we can write the vector $\hat{\mathbf{L}}_k$ in the following form,

$$\hat{\mathbf{L}}_k = \tilde{\mathbf{L}}_0 + \sum_{i=1}^{k} \mathbf{s}_i + \sum_{j=1}^{m-1} \mathbf{c}_j, \tag{9}$$

where $\tilde{\mathbf{L}}_0$ is the initial location guess, $\mathbf{s}_i$ is the i^{th} step estimation with random errors in stride length and orientation, and $\mathbf{c}_j$ is the j^{th} correction based on range information. Although $\sum_{j=1}^{m-1} \mathbf{c}_j$ can effectively reduce the uncertainty caused by $\sum_{i=1}^{k} \mathbf{s}_i$, the error cannot be fully eliminated in general. More importantly, the accumulated random error in the step vectors since the $(m-1)^{\text{th}}$ correction has not been taken care of yet. Therefore, if we treat each step as an independent event, we can apply Central Limit Theorem (CLT) on $\hat{\mathbf{L}}_k = [\hat{x}_k, \hat{y}_k]^T$, and model $[\hat{x}_k, \hat{y}_k]^T$ as bivariate Gaussian random variables with mean $[x_k, y_k]^T$, and variances σ_x^2 and σ_y^2.

On the other hand, the parametric form of $f(r_{m,n}|\mathbf{L}_k)$ is dependent on the technology being used for the ranging sub-system. For example, the error of Time-of-Arrival (ToA) based ranging system using RF signals has been modelled as a Gaussian random variable in [2]. In some cases, when the ranging technology employed has very fine resolution and the tracking service has very tight delay constraints, the range measurement can be simply treated as deterministic in order to reduce the computational overhead. In the next sub-section, we examine this special case where a fine-resolution and stable ranging technology is used.

Algorithm 1 Generalized Fusion Algorithm

initialize:
if initial location is given as $[x_0, y_0]^T$ **then**
  $\tilde{\mathbf{L}}_0 = [x_0, y_0]^T$
else
  if a range measurement, $r_{1,n}$, is obtained **then**
    $\tilde{\mathbf{L}}_0 = \underset{\mathbf{L}_0}{\operatorname{argmax}}\{f(r_{1,n}|\mathbf{L}_0)\}$
  end if
end if
k^{th} iteration:
if a step is detected with orientation θ_k **then**
  compute step displacement by (4)
  update location estimation by (5)
else
  if a range measurement, $r_{m,n}$, is obtained **then**
    $\tilde{\mathbf{L}}_k = \underset{\mathbf{L}_k}{\operatorname{argmax}}\{f(\hat{\mathbf{L}}_k|\mathbf{L}_k) \cdot f(r_{m,n}|\mathbf{L}_k)\}$
  end if
end if

C. Simplified Correction Scheme for Fine-resolution Range Sensor

When the m^{th} range measurement from the n^{th} BN is deterministic, the user can only appear on a circle with radius $r_{m,n}$ centering $[x_n^{\text{B}}, y_n^{\text{B}}]^T$. Therefore, the ML correction scheme is reduced to simply finding the location $\tilde{\mathbf{L}}_k$ which maximizes the likelihood, $f(\hat{\mathbf{L}}_k|\ ||\tilde{\mathbf{L}}_k - [x_n^{\text{B}}, y_n^{\text{B}}]^T|| = r_{m,n})$.

Recall that $\hat{\mathbf{L}}_k = [\hat{x}_k, \hat{y}_k]^T$ is assumed to be bivariate Gaussian random variables. Numerically, at any point $[x', y']^T$ on the circle centering $[x_n^{\text{B}}, y_n^{\text{B}}]^T$ with radius $r_{m,n}$, the Gaussian Likelihood can be computed for $[\hat{x}_k, \hat{y}_k]^T$, with mean $[x', y']^T$, and variances σ_x^2 and σ_y^2. The point which yields the highest likelihood value is picked as the corrected position.

Note that, if we assume σ_x^2 and σ_y^2 to be equal, the ML correction scheme further reduces to simply finding the point on the circle with the shortest Euclidean distance to $\hat{\mathbf{L}}_k$.

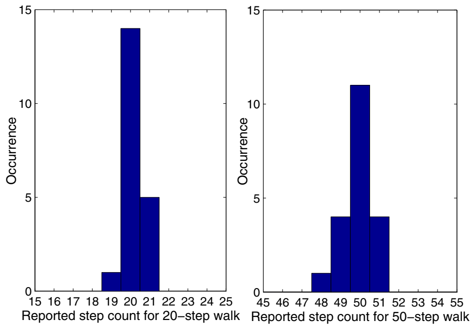


Fig. 6. Histograms of the digital step counter output.

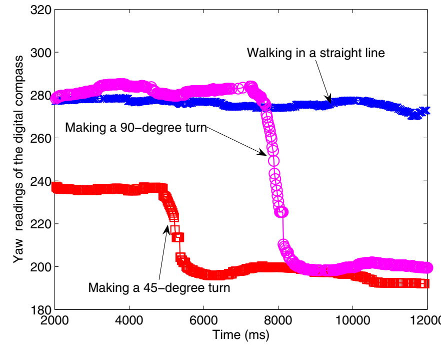


Fig. 7. Yaw readings of digital compass for different walking scenarios.

V. Experimental Verifications and Discussion

A. Sensor Evaluation and Calibration

1) Digital Step Counter: In order to evaluate the performance of the digital step counter, we conducted experiments in which a user took twenty 20-step walks and twenty 50-step walks, respectively, hand-holding the G1 phone on which the step counter is implemented. The histograms of the digital step counter's output are shown in Fig. 6. The simple digital step counter that we implemented is able to count the steps taken by the user within an error of one step most of the time.

2) Stride Length Calibration: The stride length l is modelled as a random variable which is independent and identically distributed (iid) for each step. The mean of l is used for displacement estimation. We carried out experiments in which a user takes fifty 20-step walks indoor with normal walking speed. The mean and variance of the distance covered by 20 steps over the 50 trials are 13.66 m and 0.03 m^2 respectively. So the mean and standard deviation of one step's stride length are $\frac{13.66}{20} = 0.68$ m and $\sqrt{\frac{0.03}{20}} \approx 0.038$ m according to the property of iid random variables. The standard deviation per meter can be roughly estimated as $\frac{0.038}{0.68} \approx 0.057$ m/meter. It is more than 50 times larger than that of the wheel encoder used in [17], which has standard deviation of 0.001m/meter.

It is important to note that, even if we use an ideal step counter which always detects the correct number of steps, the irregularity and variations of human walking will still introduce much larger deviations than vehicles or wheeled robots with fine accuracy wheel encoders. Advanced adaptive stride estimation schemes, such as [18], have achieved closer walking distance estimations than a simple fixed stride scheme. However, the errors are on the same order of magnitude.

3) Digital Compass: Fig. 7 shows the digital compass yaw readings for three typical walking scenarios, namely, a straight-line walking path, a walking-path involving a 45 degree turn, and a walking path involving a 90 degree turn. As can be seen in the figure, the digital compass readings are able to reflect the actual change of user orientation. The error and instability in the direction measurement are caused by factors such as the electronic noise in the device, the presence of metal furniture or other electronic equipment which creates EM fields, and irregular movement of the user's arms and hands.

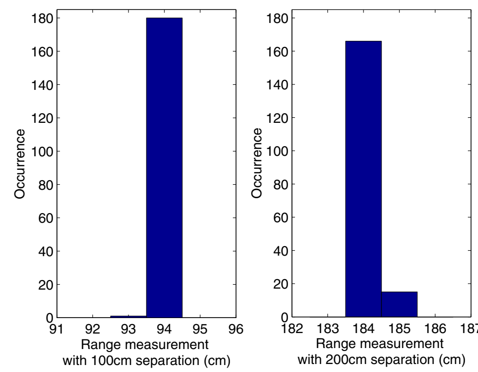


Fig. 8. Histograms for range measurement with 1m (left) and 2m (right) separations.

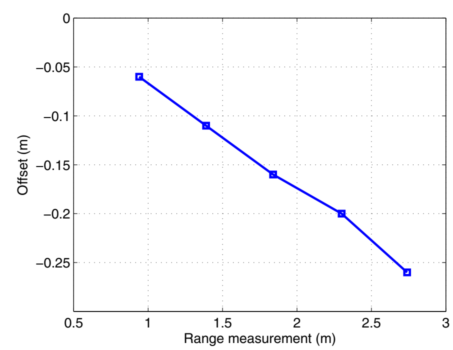


Fig. 9. Error in range measurement vs. reported range.

4) Range Sensor: Fig. 8 shows the histograms for the Cricket ranging data with BN-LN separation of 1 m and 2 m respectively. In both cases, the reported distances have negligible variances. With 1 cm resolution, the distance measurement can be treated as deterministic. Therefore, the specialized fusion scheme described in Section IV-C can be applied.

As also can be observed in Fig. 8, both distance measurements have some offsets from the true separation. Through experiments, we have discovered that there is a near-linear relationship between the measurement offset from the true distance and the distance measurement itself. Therefore, the offset can be easily compensated for any calibrated BN-LN combinations. The offset-measurement relationship is plotted in Fig. 9 for a particular BN-LN combination.

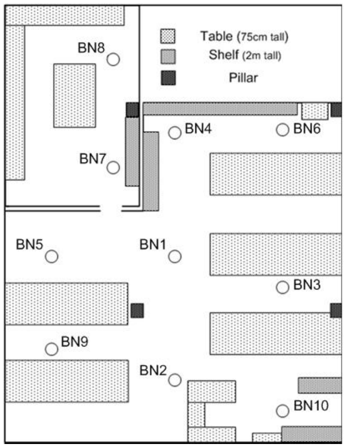


Fig. 10. The experimental testbed.

B. Testbed Setup and Infrastructure Configuration

In order to evaluate the tracking performance of the proposed scheme, we have chosen one laboratory on our campus as the indoor tracking testbed. The testbed is 16.9 m$\times$13.2 m in dimension. It contains a common working area and a meeting room. The layout of the testbed is shown in Fig. 10 with locations of tables and shelves indicated.

There are 10 Cricket BNs installed on the ceiling in the testbed as the ranging infrastructure, as indicated in Fig. 10. The height of the ceiling is 2.5 m. In order to minimize the collision between BN's RF frames, we implemented a simple TDMA-based BN transmission scheduling protocol. BN 1 will transmit its RF packet (and the ultrasound pulse) every one second. Upon hearing BN 1's RF packet, BN n will wait for $t_w \cdot (n-1)$ amount of time before its own transmission. In our system, since there are 10 BNs, t_w is chosen to be 100 ms.

One Cricket Mote functioning as the LN is carried along by the mobile user together with the HTC G1 phone. The height of the LN is kept at 1.2 m. Whenever a range measurement, r_n, is made with respect to BN n at time t, an RF packet containing r_n, n, and t will be sent to another Cricket Mote, labelled as the "Base Station", which is connected to a PC.

Through calibration, we have found that, although the RF beacon can be heard over a long distance, the ultrasound emitted by a BN mounted on the ceiling cannot be heard by a LN with 1.2 m height at a horizontal distance larger than 2.5 m. Therefore, due to our sparse testbed setup, the LN can measure the distance from *at most one* infrastructure BN at any given time instance. Moreover, the raw range measurements after compensation are only treated as valid if they fall in the range, $[1.3\text{m}, 2.8\text{m}]$ (because $\sqrt{1.3^2+2.5^2} \approx 2.8$ (m)). We note that invalid readings may be caused by receiving reflected ultrasound signals.

C. Synchronization of Sub-systems

Since the DR sub-system and the ranging sub-system are implemented on separate hardware with different system clocks, the synchronization between these two sub-systems is critical for correct operation. For the convenience of off-line study, we synchronize both sub-systems to a desktop PC.

For the ranging sub-system, the LN reports its local timestamp t_c to the PC by sending a synchronization message through the RS-232 serial connection. The PC will record down its local timestamp t_{PC} when the LN's synchronization message is received. The clock offset for the ranging sub-system is computed as $\Delta_c = t_{PC} - t_c$. The synchronization between the phone and the PC is accomplished wirelessly through TCP socket connection. The PC will send a synchronization message SYNC1 to the phone and record down the sending time t_1. Upon receiving SYNC1, the phone sends a synchronization message SYNC2 containing its local timestamp t_p back to the PC through the on-device Wi-Fi. The PC records the receiving time of SYNC2 as t_2. If we assume that both SYNC1 and SYNC2 spend almost the same amount of time travelling between the PC and the phone, the time offset between the phone and the PC can be computed as $\Delta_p = (t_1+t_2)/2 - t_p$.

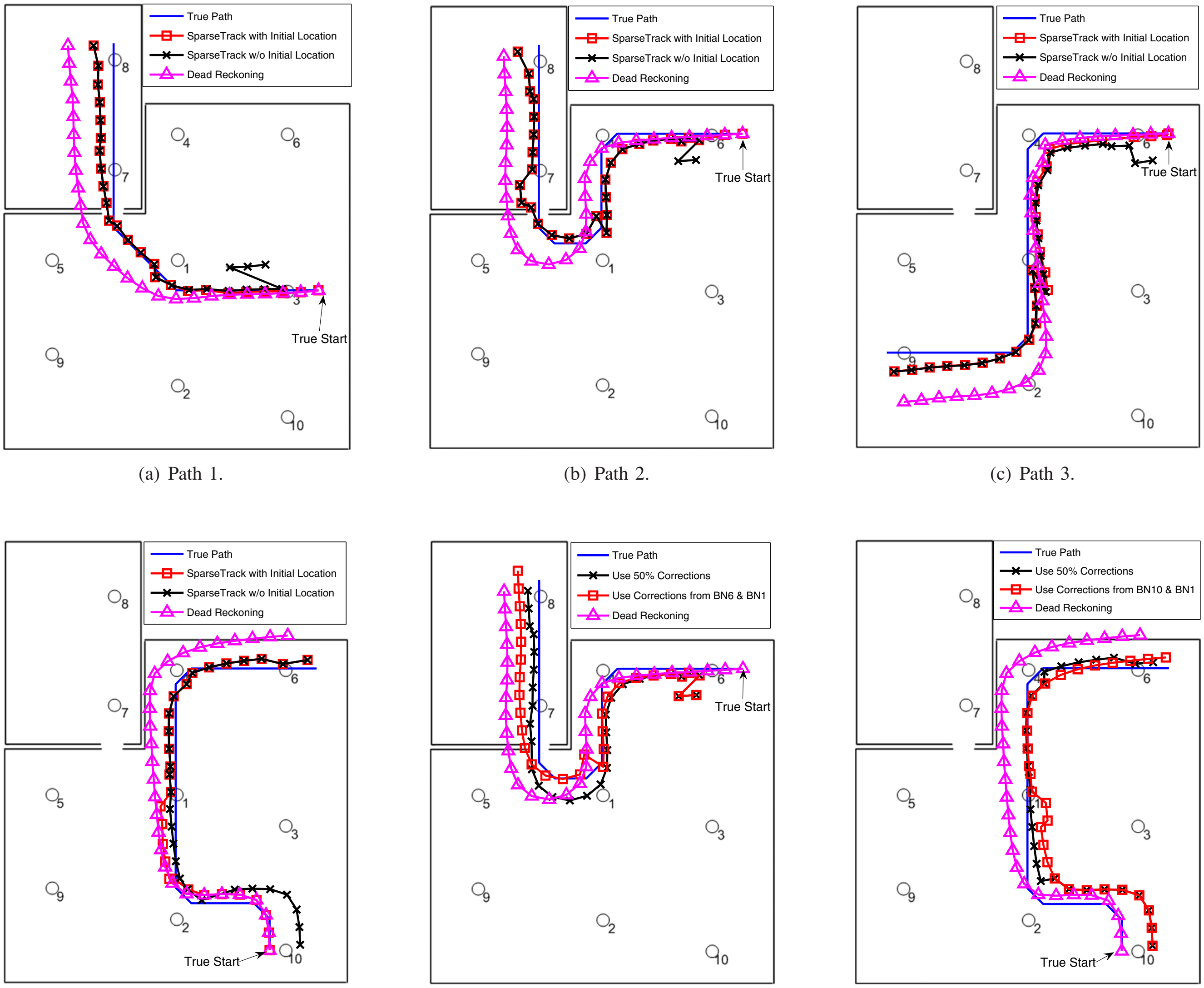
D. Tracking Performance

Four walking paths are chosen in the testbed to evaluate the tracking performance of the proposed SparseTrack system. A user holding the sensors walks through the paths at normal speed. The stride length and step detection threshold of the user are pre-calibrated.

We use the average error between the estimated path and the actual path as the performance metric. Even though our experiments are carried out over preplanned paths, it is still difficult to know the ground truth of the user location at any exact time instance. Hence, we compute the average tracking error by computing the area between the true path and the estimated path, and normalizing it by the true path length.

First, we compare the tracking performance of the proposed SparseTrack system, with and without the knowledge of the initial location, to that of the DR system. The trajectories estimated by these three schemes for the four paths are shown in Fig. 11(a)-11(d). As can be seen in the figures, although a digital step counter is used for DR instead of directly integrating accelerometer measurements for displacement estimation, the tracking error of the DR system still accumulates over time. As a result, there is a large offset between the DR estimation and the true user location at the end of each path.

On the other hand, the proposed scheme can effectively constrain the error accumulation with the aid of the sparse ranging infrastructure. Occasionally, when a range measurement r is available from a certain BN, n, the user location is adjusted to the closest point on the circle centering BN n with radius r. The adjustment can be observed from the figures when the error accumulated before range measurement is large. More interestingly, when the initial location is unknown, SparseTrack starts tracking with a random point on a circle whose radius and center are the first range measurement and the first BN heard, respectively. As shown in the figures, the path estimated without knowledge of the initial location converges rapidly towards the estimation made when the initial location is given.



(a) Path 1. (b) Path 2. (c) Path 3.

(d) Path 4. (e) Path 2 with increased sparsity. (f) Path 4 with increased sparsity.

Fig. 11. Figures (a)-(d) present the estimated trajectories for DR and SparseTrack with and without initial location. Figures (e)-(f) present the estimated trajectories with increased sparsity.

Table I summarizes the average error and the average rate at which the corrections are made, when all valid range measurements are used for corrections. As can be seen, SparseTrack outperforms the DR with reduction in average tracking errors by at least 31.51% even when the initial location is unknown to it. When the initial location is known to SparseTrack, the reduction in average error can be as much as 71.88%. Such an improvement in the tracking performance is obtained using range corrections at a rate of less than once per second.

Next, we study the robustness of the tracking performance of SparseTrack in two typical scenarios in which the range measurements from infrastructure BNs are extremely sparse. In the first scenario, beacon frames are lost due to wireless interference. We emulate this by letting the user device decide *randomly* whether to make a correction whenever a range measurement becomes available, with 50% probability. Sparsity in the second scenario is simply due to the lack of infrastructure BNs; we emulate this by only allowing corrections based on range measurements from two of the ten BNs *deterministically*. Here, we are assuming the initial location is unknown. Therefore, one of the BNs must be the one from which the first range measurement is made after the user appears in the testbed. The second BN is chosen to be the one installed in the center of our testbed. The performance of SparseTrack in these two scenarios are tested with two paths and compared with the DR scheme (to which the initial location is given). The estimated trajectories are shown in Fig. 11(e) and 11(f). We also present the average error and average rate of corrections in Table II for these two scenarios. As shown in Table II, with a very sparse infrastructure, although the rate of correction can be as low as 0.24 times per second, the reduction in tracking error compared to DR is still significant. In particular, on path 4, for a 42% decrease in correction rate, we only see an 8% increase in average tracking error when corrections are randomly accepted. For deterministic correction acceptance, we see a 34% increase in error for a 58% decrease in correction

TABLE I
COMPARISON OF AVERAGE ERROR AND RATE OF CORRECTIONS

	Path 1	**Path 2**	**Path 3**	**Path 4**
Average Error of DR (m)	0.96	0.74	0.73	0.70
Average Error of SparseTrack with Initial Location (m)	0.27 (71.88%)	0.32 (56.76%)	0.41 (43.84%)	0.28 (60.00%)
Average Error of SparseTrack w/o Initial Location (m)	0.36 (62.50%)	0.37 (50.00%)	0.50 (31.51%)	0.38 (45.71%)
Average Rate of Correction (per second)	0.82	0.81	0.34	0.76

Note: The percentage values in the brackets represent the reduction in average tracking error compared to the DR approach.

TABLE II
COMPARISON OF AVERAGE ERROR AND RATE OF CORRECTIONS WITH INCREASED SPARSITY

	Path 2			**Path 4**		
	DR	**Random**	**Deterministic**	**DR**	**Random**	**Deterministic**
Average Error (m)	0.74	0.42 (43.24%)	0.48 (35.13%)	0.70	0.41 (41.43%)	0.51 (27.14%)
Average Rate of Correction (per second)	N/A	0.49	0.24	N/A	0.44	0.32

Note: The percentage values in the brackets represent the reduction in average tracking error compared to the DR approach.

rate. These results highlight the feasibility of implementing such an indoor tracking system with sparse infrastructure support in realistic situations.

VI. CONCLUSION AND FUTURE WORK

In this paper, we have proposed an indoor tracking scheme which fuses the output of a DR sub-system consisting of low cost sensors and a ranging sub-system with sparse infrastructure. We have derived a probabilistic fusion scheme for the general case in which the accuracy and resolution of the ranging sub-system may vary. In order to verify the effectiveness of the proposed system, we have implemented an indoor tracking system using the sensors on a hand-held mobile device and a reliable ranging system using Cricket technology. Experimental results have shown that, the proposed system not only delivers much better tracking performance compared to the DR approach, but also eliminates the uncertainty rapidly and provides satisfactory tracking accuracy even when the initial user location is unknown. More importantly, even with very sparse infrastructure support, in both time and space domain, the proposed scheme is still able to deliver significant improvements in tracking performance compared to DR.

We point out two future directions based on our work. First of all, ranging technology with larger uncertainty and coarser resolution, such as received signal strength based ranging with Bluetooth or WLAN, can be used as the ranging sub-system. The theoretical framework that we have proposed in this paper is general enough to incorporate such extensions. Secondly, whenever a map is available, the proposed system can be fused with map-matching algorithms in order to eliminate unlikely locations by considering the presence of walls and furniture.

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