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Fine-grained Indoor Tracking by Fusing Inertial Sensor and Physical Layer Information in WLANs

Zan Li, Danilo Burbano Acuña, Zhongliang Zhao, Jose Luis Carrera, Torsten Braun

Technischer Bericht INF-15-004 vom 22. December 2015

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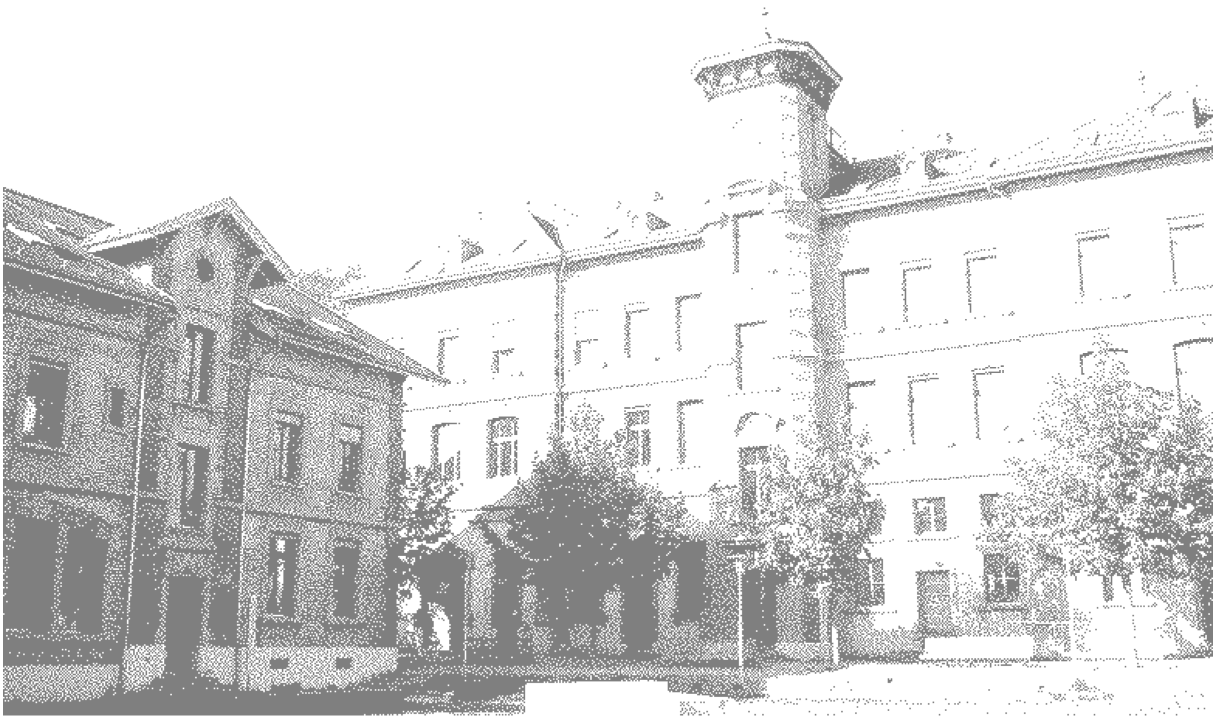

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Abstract

Indoor positioning has become an emerging research area because of huge commercial demands for location-based services in indoor environments. Channel State Information (CSI) as a fine-grained physical layer information has been recently proposed to achieve high positioning accuracy by using range-based methods, e.g., trilateration. In this work, we propose to fuse the CSI-based ranges and velocity estimated from inertial sensors by an enhanced particle filter to achieve highly accurate tracking. The algorithm relies on some enhanced ranging methods and further mitigates the remaining ranging errors by a weighting technique. Additionally, we provide an efficient method to estimate the velocity based on inertial sensors. The algorithms are designed in a network-based system, which uses rather cheap commercial devices as anchor nodes. We evaluate our system in a complex environment along three different moving paths. Our proposed tracking method can achieve $1.3m$ for mean accuracy and $2.2m$ for 90% accuracy, which is more accurate and stable than pedestrian dead reckoning and range-based positioning.

Contents

1 Introduction **1**

2 Related Work **4**

3 Particle Filters **5**

4 An Enhanced Particle Filter with Data Fusion and Weighted Likelihood **6**

4.1 Observation Model for Data Fusion 7

4.1.1 Velocity Likelihood 7

4.1.2 Ranging Likelihood 8

4.2 Weighted Likelihood for Ranging Information 8

5 Range and Velocity Estimations **10**

5.1 Range Estimation using CSI 10

5.2 Velocity Estimation using Inertial Sensors 10

5.2.1 Speed Estimation 13

5.2.2 Orientation Estimation 13

5.2.3 Velocity Estimation 14

6 Implementation of WiFi Tracking Algorithms in A Network-based System **15**

6.1 Mobile Target 15

6.2 Anchor Nodes 16

6.3 Server 16

7 Performance Evaluation **18**

7.1 Measurement Setup 18

7.2 Experiment Results 18

8 Conclusions **21**

References **22**

1 Introduction

In recent years, location based services have provided new commercial opportunities based on the locations of users. For example, shop owners can analyze the customers' buying behaviours based on their locations. To obtain these location information, GPS (Global Positioning System) is often used in outdoor environments. However, GPS signals are typically too weak to penetrate walls and hence indoor positioning techniques have attracted increasing research interests. Based on the observation parameters, previous indoor positioning research can be divided into two categories, 1) Pedestrian Dead Reckoning (PDR) based on Inertial Measurement Units (IMUs) and 2) radio-based positioning.

With the development of smart phones, PDR systems can leverage inertial sensors, e.g., accelerometer, magnetometer, and gyroscope, to estimate the relative movement of the target by detecting steps, estimating stride length and heading orientation. By integrating the estimated relative movement at sequential time intervals, PDR systems can track the target. Because of integration, small positioning errors resulting from the noise in low cost IMUs can be magnified [1].

In contrast to PDR, radio-based positioning relies on the measured radio parameters, e.g., power and time, to estimate the absolute positions of targets in a coordinate system instead of integrating the relative movement. Radio-based positioning can be classified as range-free and range-based methods. Range is defined as the propagation distance between the target and an Anchor Node (AN). Fingerprinting as one of the commonly used range-free method can provide satisfying accuracy but is very labour intensive to build up a radio map [2]. Range-based methods need to convert the measured radio parameters to range values, which is named as ranging. They are normally error prone to multipath propagation, especially with Received Signal Strength Indicator (RSSI), which is a coarse MAC layer information. Channel State Information (CSI) can be considered as a fine-grained power, which can distinguish the power from different propagation paths. It has been recently proposed to achieve highly accurate ranging, because of its ability to mitigate multipath propagation [3, 4]. After ranging, trilateration algorithms are adopted to calculate the absolute location of the target in the local coordinate system. However, trilateration algorithms normally neglect the relative movement between sequential times for a mobile target.

These two positioning methods (PDR and range-based methods) are complementary because PDR can provide information about the relative move-

ment between sequential times, i.e., velocity, which is missing in range-based methods. Additionally, the absolute location information provided by range-based methods can also be used to mitigate the accumulative errors in PDR.
In this work, we investigate how to accurately track a WiFi target using an enhanced particle filter to fuse the velocity information estimated by inertial sensors and highly accurate range information by some enhanced ranging methods. Our main scientific contributions are summarized as follows.

- We propose an enhanced particle filter to fuse the CSI-based ranging and velocity information. The two observation parameters, i.e., ranges and velocity, are fused in the observation likelihood function defined in Section 3. To achieve high ranging accuracy, some enhanced CSI-based ranging methods, which were proposed in our previous work [4], are adopted in our proposed particle filter. Additionally, we adopt the spatial diversity between different antennas to mitigate the multipath effect in the ranging step in this work. To mitigate the influence of the ranging errors, a weighting technique is introduced in the observation likelihood function. Furthermore, we propose an efficient method to estimate the velocity of the mobile target using the timestamped values from the accelerometer and compass sensors in a smart phone.

- We implement a network-based positioning system, which runs our proposed tracking algorithms in a central server. Compared to terminal-based positioning system, a network-based positioning system is able to run algorithms with high complexity and analyze multiple users' movement paths. In our system, all ANs are implemented on cheap commercial devices and are able to collect inertial sensor and CSI information from the received WiFi packets.

- We evaluate our system in a complex environment along three different moving paths. Our proposed tracking method can achieve $1.3m$ for mean accuracy and $2.2m$ for 90% accuracy, which is more accurate and stable than PDR and range-based positioning methods.

In the remainder of the paper, related works are reviewed in Section 2. Some preliminaries for particle filters are introduced in Section 3. Our main contributions are introduced in Section 4, in which the proposed enhanced particle filter is described. The ranging and velocity estimation mechanisms are presented in Section 5. Section 6 presents the implementation of the proposed algorithms in a network-based indoor tracking system. Section 7 presents the evaluation results in a complex indoor environment. Finally, Section 8 concludes the paper.

2 Related Work

Inertial sensors have been intensively investigated for indoor tracking due to fast development of smart phones. Positioning with a smart phone can leverage the inertial sensors to estimate the target's moving state and locate the user. The authors of [5] investigated the mechanisms for PDR-based tracking including step detection, stride length estimation, and direction estimation. The stride length estimation method in [5] forms the basis of moving speed estimation in our work. The authors of [6] provided a system called Zee, which adopts inertial sensors and crowdsouring to achieve a calibration free WiFi-based positioning system. The authors of [1] proposed a Wap system, in which particle filter is used to fuse inertial sensor information and RSSI of WiFi signals for tracking. Different from our work, they only use the relative changes of RSSI instead of ranges based on CSI to discover the direction changes and improve room distinguishing algorithms because the measured RSSI is a coarse and unstable parameter.

Channel state information can be considered as a fine-grained power information and has been firstly proposed by the authors of [7] in a prototype called FILA, in which channel state information is investigated to estimate the range information and a simple trilateration algorithm with Linear Least Square (LLS) is further adopted to locate the target. FILA has demonstrated that channel state information can mitigate multipath propagation and impressively improve the localization accuracy compared to RSSI. In FILA, the target laptop is equipped with an off-the-shelf WiFi network card (IWL5300) to extract CSI based on an improved firmware [8]. In our previous work [4], we proposed a passive indoor positioning system, which can extract channel state information from the overheard packets based on software defined radio techniques. In that work, we proposed an enhanced trilateration algorithm, which combines Weighted Centroid and Constrained Weighted Least Square (WC-CWLS). The algorithm outperforms LLS for static targets. Although both works [7, 4] evaluated the proposed trilateration algorithms for mobile targets, they did not consider Bayesian estimation methods, i.e., Kalman filter and particle filter, which are more accurate to track mobile targets. Additionally, CSI has been investigated for fingerprinting methods and velocity estimation. In [9], the authors provided a network-based indoor tracking system, which estimates the velocity of a mobile target from CSI and locates the target by fingerprinting based on CSI.

3 Particle Filters

We consider the problem of tracking the location of a mobile target over time given a stream of noisy observations, e.g, ranges and velocity. Thus, at time k, we have an unknown system state vector $\mathbf{x}_k$ including the target's location (or some other parameters related to the target's moving state, e.g., velocity) and a discrete sequence of noisy measurement vectors $\mathbf{z}_{1:k}$, taken at times $1, \ldots, k$.
The target moves according to a non-linear function:
$\mathbf{x}_k = \mathbf{f}_k(\mathbf{x}_{k-1}, \mathbf{v}_k)$, **(system model)**
and the measurement system observes the target according to another non-linear function:
$\mathbf{z}_k = \mathbf{h}_k(\mathbf{x}_k, \mathbf{u}_k)$, **(observation model)**
where $\mathbf{v}_k$ and $\mathbf{u}_k$ are the system and measurement noise.
From a Bayesian perspective, the goal is to calculate the "degree of belief" $p(\mathbf{x}_k|\mathbf{z}_{1:k})$ in the current state of the system $\mathbf{x}_k$, based on the available measurements $\mathbf{z}_{1:k}$ and an initial Probability Distribution Function (PDF) $p(\mathbf{x}_0)$ [10]. This degree of belief is the posterior PDF over the state space of our system.
In contrast to Kalman filters, which assume a Gaussian posterior PDF, particle filters can deal with a non-Gaussian posterior PDF via Monte Carlo simulations, which represent the required posterior PDF by a set of random samples with *associated weights*. Based on Monte Carlo methods, the posterior PDF $p(\mathbf{x}_k|\mathbf{z}_{1:k})$ can be estimated by the following delta function:

$$p(\mathbf{x}_k|\mathbf{z}_{1:k}) \approx \sum_{i=1}^{N_s} w_k^i \delta(\mathbf{x}_k - \mathbf{x}_k^i), \tag{1}$$

where $\mathbf{x}_k^i$ is the ith particle and w_k^i is the *associated weight*. N_s is the total number of particles. For Bootstrap Particle Filter (BPF) [11], which is commonly used and efficiently implementable, the associated weights can be calculated as:

$$w_k^i \propto w_{k-1}^i \cdot p(\mathbf{z}_k|\mathbf{x}_k^i), \tag{2}$$

in which the associated weights are only determined by the *likelihood* function of $p(\mathbf{z}_k|\mathbf{x}_k^i)$.

4 An Enhanced Particle Filter with Data Fusion and Weighted Likelihood

As introduced in Section 1, tracking methods by using power-based ranging and PDR are complementary. Hence, we propose an enhanced particle filter to fuse these velocity and range information to provide a tracking method with high accuracy and stability in this section.
In this work, a Constant Velocity (CV) model is used. The state vector is defined as,

$$\mathbf{x} = [x, y, v_x, v_y]^T, \tag{3}$$

where (x, y) are the Cartesian coordinates of the target and (v_x, v_y) is a two-dimensional moving speed vector. Under the CV model, the prediction function can be written as,

$$\mathbf{x}_k = \mathbf{F} \cdot \mathbf{x}_{k-1} + \boldsymbol{\eta}\mathbf{w}, \tag{4}$$

where

$$\boldsymbol{\eta} = \begin{pmatrix} \Delta T^2/2 & 0 \\ 0 & \Delta T^2/2 \\ \Delta T & 0 \\ 0 & \Delta T \end{pmatrix}, \mathbf{F} = \begin{pmatrix} 1 & 0 & \Delta T & 0 \\ 0 & 1 & 0 & \Delta T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}.$$

ΔT is the time interval between two subsequent estimations of the target location and $\mathbf{w}$ is a 2×1 independent and identically distributed (i.i.d.) process noise vector. In particle filters, each particle $\mathbf{x}_k^i$ is updated based on Equation (4) from the particles at the previous moment $\mathbf{x}_{k-1}^i$.

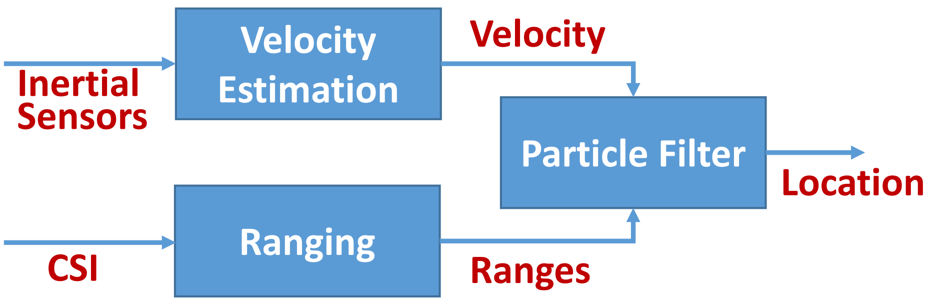


Figure 1: Data Fusion via a Particle Filter

4.1 Observation Model for Data Fusion

After updating particles based on Equation (4), the associated weight w_k^i should be updated from the weight at the previous moment w_{k-1}^i based on the likelihood of the observations conditioned on each particle $p(\mathbf{z}_k|\mathbf{x}_k^i)$ (Equation (2)). In this work, the observation vector obtained at each time interval contains an estimation of ranges to different ANs and velocity of the mobile target. Subsequently, the measurement vector is given as $\mathbf{z}_k = [\mathbf{d}_k, \mathbf{v}_k]$, where $\mathbf{d}_k$ includes ranges to N different ANs and $\mathbf{v}_k$ is the velocity information from the inertial sensors.

To fuse the range information $\mathbf{d}_k$ and velocity information $\mathbf{v}_k$, we can reasonably assume that the velocity information $\mathbf{v}_k$ is independent from ranges because the range information depends on the location of target but velocity does not. Hence, the likelihood $p(\mathbf{z}_k|\mathbf{x}_k^i)$ can be written as

$$p(\mathbf{z}_k|\mathbf{x}_k^i) = p(\mathbf{d}_k|\mathbf{x}_k^i) \cdot p(\mathbf{v}_k|\mathbf{x}_k^i). \tag{5}$$

In order to distinguish different likelihoods, we refer to $p(\mathbf{z}_k|\mathbf{x}_k^i)$ as the overall likelihood, $p(\mathbf{d}_k|\mathbf{x}_k^i)$ as the ranging likelihood, and $p(\mathbf{v}_k|\mathbf{x}_k^i)$ as the velocity likelihood.

With this method, the associated weight w_k^i can be updated by considering both range and velocity observations. On one hand, the particles at the absolute positions (x^i, y^i), which have low probabilities to observe the measured ranges $\mathbf{d}_k$, will be assigned small associated weights to suppress their contributions to the state estimation. On the other hand, the particles with velocities (v_x^i, v_y^i), which have low probabilities to observe the measured velocity $\mathbf{v}_k$, will be also assigned small associated weights, especially for some particles with unusual large moving speeds in indoor environments. This will allow smoothing the estimated moving paths.

4.1.1 Velocity Likelihood

As we work on a two-dimensional tracking system, the measured velocity information $\mathbf{v}_k$ is a vector with two components $\hat{v}_x$ and $\hat{v}_y$, which can be measured from inertial sensors. Assuming that these two components are independent from each other, the velocity likelihood $p(\mathbf{v}_k|\mathbf{x}_k^i)$ can be written as

$$p(\mathbf{v}_k|\mathbf{x}_k^i) = p(\hat{v}_{x,k}|\mathbf{x}_k^i) \cdot p(\hat{v}_{y,k}|\mathbf{x}_k^i). \tag{6}$$

Additionally, these two velocity components are independent from the coordinate components (x, y) in each particle. Hence we can obtain that $p(\hat{v}_{x,k}|\mathbf{x}_k^i) = p(\hat{v}_{x,k}|v_{x,k}^i)$ and $p(\hat{v}_{y,k}|\mathbf{y}_k^i) = p(\hat{v}_{y,k}|v_{y,k}^i)$. The estimation of each velocity component is assumed to follow a Gaussian distribution. Equation (6) can be written as

$$\begin{aligned} p(\mathbf{v}_k|\mathbf{x}_k^i) &= p(\hat{v}_{x,k}|v_{x,k}^i) \cdot p(\hat{v}_{y,k}|v_{y,k}^i) \\ &= \frac{1}{\sigma_v\sqrt{2\pi}}\text{exp}[-\frac{(\hat{v}_{x,k}-v_{x,k}^i)^2+(\hat{v}_{y,k}-v_{y,k}^i)^2}{2\sigma_v^2}], \end{aligned} \tag{7}$$

where σ_v is the variance of velocity estimation.

4.1.2 Ranging Likelihood

Besides velocity information, range information is another observation input. Assuming that ranges to different ANs are independent from each other, the ranging likelihood can be written as

$$p(\mathbf{d}_k|\mathbf{x}_k^i) = \Pi_{j=1}^N p(\hat{d}_{j,k}|\mathbf{x}_k^i), \tag{8}$$

where $\hat{d}_{j,k}$ is the estimated range to the ith AN at the kth moment. In the remainder of the paper, we refer to $p(\hat{d}_{j,k}|\mathbf{x}_k^i)$ as individual likelihood.
Because the range information exclusively depends on the location of the target, the observation function for range can be defined as:

$$\hat{d}_j = \sqrt{(x-x_j)^2+(y-y_j)^2} + u_j, \tag{9}$$

where (x_j, y_j) are the coordinates of the jth AN and u_j is a Gaussian noise with a variance of σ_j. Each individual likelihood can be written as

$$p(\hat{d}_{j,k}|\mathbf{x}_k^i) = \frac{1}{\sigma_j\sqrt{2\pi}}e^{-\frac{[\hat{d}_{j,k}-\sqrt{(x^i-x_j)^2+(y^i-y_j)^2}]^2}{2\sigma_j^2}}. \tag{10}$$

4.2 Weighted Likelihood for Ranging Information

Range estimation $\hat{d}_{j,k}$ is often shifted from the ground truth range $d_{j,k}$. Correspondingly the individual likelihoods $p(\hat{d}_{j,k}|\mathbf{x}_k^i)$ from different ANs are often biased from the real individual likelihoods $p(d_{j,k}|\mathbf{x}_k^i)$. The ranges estimated by different ANs normally face different ranging errors, especially in a complex indoor environment with mixed Line Of Sight (LOS) and Non-LOS (NLOS) conditions. Equation (8) treats all the individual likelihoods

from different ANs equally. This oversimplification introduces large estimation errors, because in the inaccurate individual likelihoods $p(\hat{d}_{j,k}|\mathbf{x}_k^i)$ from certain ANs with large ranging errors will significantly affect the accuracy of the ranging likelihood estimation $p(\mathbf{d}_k|\mathbf{x}_k^i)$.
To mitigate the influence of the large ranging errors on the estimation of the ranging likelihood $p(\mathbf{d}_k|\mathbf{x}_k^i)$, we propose to adopt a weighting technique on the ranging likelihood $p(\mathbf{d}_k|\mathbf{x}_k^i)$ estimation by suppressing the emphasis on the individual likelihoods $p(\hat{d}_{j,k}|\mathbf{x}_k^i)$ with larger ranging errors and magnifying the contributions of the individual likelihoods with smaller ranging errors. To achieve this, we provide a weighted-likelihood BPF with exponential weights on each individual likelihood from different ANs as

$$p(\mathbf{d}_k|\mathbf{x}_k^i) = \Pi_{j=1}^{N} p(\hat{d}_j|\mathbf{x}_k^i)^{m_j}, \tag{11}$$

where m_j is the *exponential weight* for the individual likelihood of the jth AN. To reduce the contribution of the individual likelihoods with large ranging errors, a direct way is to set weights m_j to indicate the error of each range. However, we can not measure the real ranging errors in practice, because it requires the ground truth location of the target.
Therefore, we need to find a suboptimal solution to set a proper value for each exponential weight. In general, range errors increase with the estimated range values. Therefore, instead of relying on the ranging errors, we can use the estimated ranging outputs to infer their corresponding errors and set the exponential weights to be inversely proportional to the estimated range outputs as

$$m_j = \frac{1/d_j}{\sum_{n=1}^{N} 1/d_n}, \tag{12}$$

which are normalized by $\sum_{j=1}^{N} m_j = 1$. With this weighting technique, we expect to mitigate the influence of ranging errors, especially for NLOS propagation, whose ranging errors are normally larger than for LOS conditions. In the remainder of this paper, we refer to the Particle Filter with data Fusion and Weighted likelihood as FW-PF.

Figure 2: Range Estimation using CSI

5 Range and Velocity Estimations

This section introduces how to estimate the two observation parameters (ranges and velocity) in our proposed particle filter.

5.1 Range Estimation using CSI

More accurate estimation of ranges is a prerequisite to improve the radio-based tracking accuracy. To achieve high ranging accuracy, we adopt the same method as our previous work [4], which uses channel state information to extract the Power from the Direct Path (PDP). Figure 2 shows the procedure of this ranging method, which comprises three steps. First, CSI in frequency domain is converted to CIR (Channel Impulse Response) in time domain by Inverse Fast Fourier Transform (IFFT). Second, PDP is obtained by extracting the strongest power in CIR. Finally, a NLR (Non-Linear Regression) model is adopted to calculate the range information from PDP. Please find details about this ranging method in our previous work [4].

Additionally, most recent WiFi standards (IEEE 802.11n/ac standards) support MIMO (Multiple Input and Multiple Output), which introduces spatial diversity. Multiple antennas separated by certain distances normally face different multipath effects. Therefore, we can exploit multiple antennas to smooth and mitigate the multipath effects. In our work, we estimate the range information based on the procedures in Figure 2 on each antenna and then calculate the average range from all the antennas in one AN as the input range information to the particle filter.

5.2 Velocity Estimation using Inertial Sensors

Velocity is another observation input in our proposed particle filter. In our work, the velocity of the mobile target is estimated by analyzing the timestamped values of inertial measurement units in a smart phone. To estimate the two-dimensional velocity, which is a vector value with two components

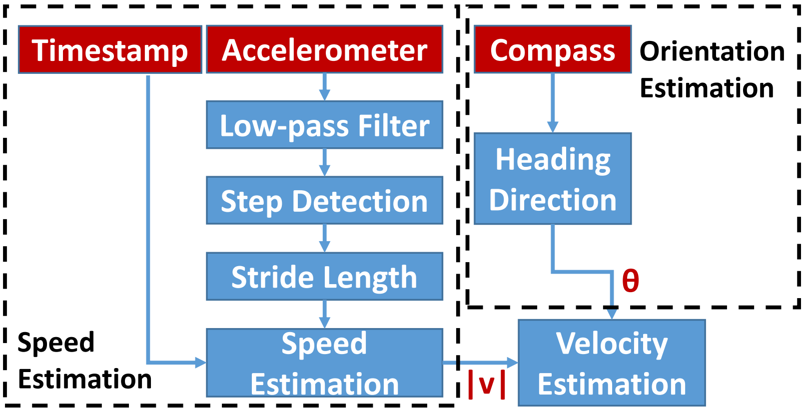


Figure 3: Velocity Estimation

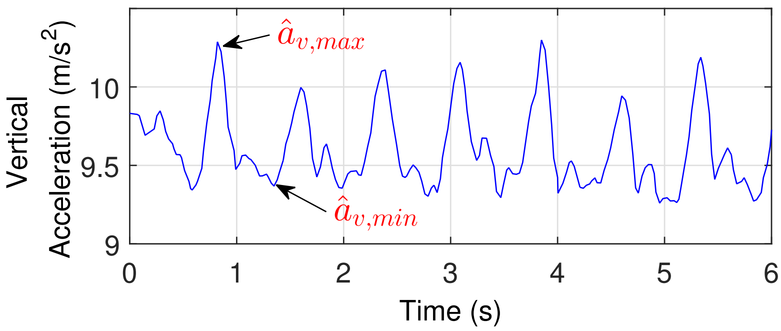
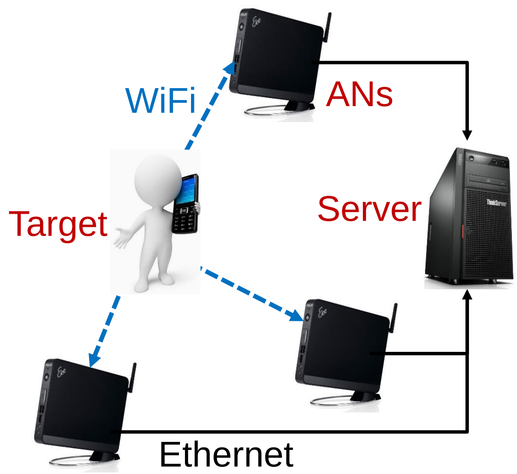
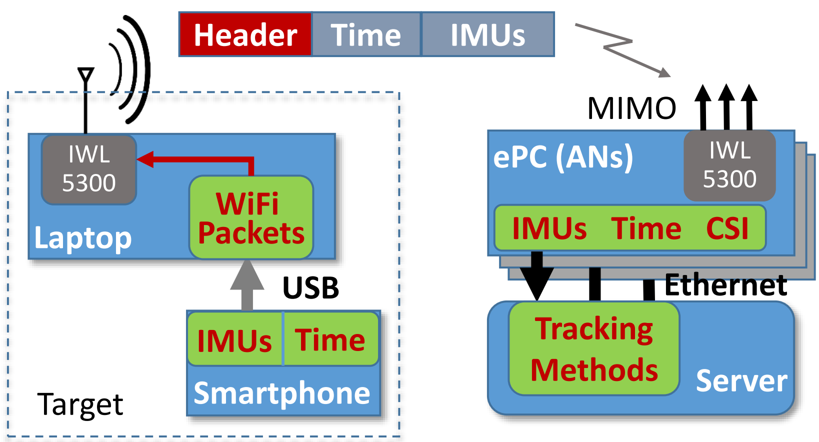


Figure 4: Vertical Acceleration



(a) Overview of the System



(b) Implementation of the System

Figure 5: Network-based Tracking System

on x and y axes in a Cartesian coordinate system, the heading orientation θ and speed $|v|$, which is the absolute value of velocity, are estimated based on compass and accelerometer respectively.

5.2.1 Speed Estimation

As shown in Figure 3, first, the raw values from the accelerometer are smoothed through a low pass filter using Equation (13) to mitigate the influence of noise and dynamic pushes.

$$\hat{a}_{v,i} = (1 - \beta)a_{v,i} + \beta(\hat{a}_{v,i-1}), \tag{13}$$

where $a_{v,i}$ is the raw vertical acceleration and β is a constant value ranging from 0 to 1 (0.9 in our work).
Second, during walking, every step generates one peak and dip in the measured vertical acceleration $\hat{a}_{v,i}$ as shown in Figure 4. Therefore, we can detect the dips and peaks from $\hat{a}_{v,i}$ as steps.
Third, Equation (14) is used to estimate stride length [5].

$$l = K(\hat{a}_{v,max} - \hat{a}_{v,min})^{1/4}, \tag{14}$$

where l is stride length, $\hat{a}_{v,max}$ and $\hat{a}_{v,min}$ are the peak and dip values of $\hat{a}_v$ on each stride respectively, and K is a coefficient calibrated for individuals.
Fourth, because all the accelerometer values are timestamped in the smart phone, we can calculate the time interval for each stride ΔT and the speed can be calculated as

$$|\mathbf{v}| = \frac{l}{\Delta T}. \tag{15}$$

5.2.2 Orientation Estimation

To estimate the heading orientation, we adopt the compass [12] in smart phones, which derives its data from the accelerometer and magnetometer. The compass reports a value called azimuth α, which is the clockwise angle from the north. After obtaining α, we need to calibrate α to our local coordinate system as

$$\theta = (90^\circ - \alpha) + \varphi, \tag{16}$$

where $(90^\circ - \alpha)$ is to rotate the azimuth α to the counter-clockwise angle from the east and φ is the counter-clockwise angle from +x in the local coordinate system to the east.

5.2.3 Velocity Estimation

After estimating the speed and heading orientation of the mobile target, we can get the velocity as

$$\mathbf{v} = [|\mathbf{v}|\cos(\theta), |\mathbf{v}|\sin(\theta)], \tag{17}$$

where $|\mathbf{v}|\cos(\theta)$ and $|\mathbf{v}|\sin(\theta)$ are the x and y components of moving velocity respectively.

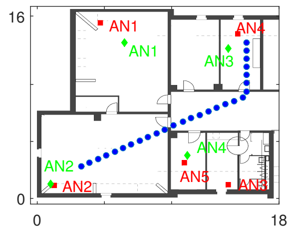
6 Implementation of WiFi Tracking Algorithms in A Network-based System

We have implemented a network-based indoor tracking system, in which our proposed tracking algorithms are running in a central server. Figure 5(a) presents the overview of this system, which comprises three main components: target, ANs, and server. Figure 5(b) shows the implementation details of each component. The main idea behind this system is that by integrating the inertial sensor information (IMUs in Figure 5(b)) in the payload of WiFi packets broadcast from the target, the server can read these IMU information from the received packets, extract the CSI information from commercial WiFi cards (Intel WiFi Wireless (IWL) 5300) in ANs, and finally track the target with these two pieces of information.

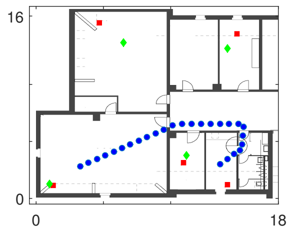
6.1 Mobile Target

The mobile target needs to 1) inject the timestamped IMU information from the smart phone into the payload of the WiFi packets and 2) broadcast these packets using monitoring mode with an 802.11n High Throughput (HT) rate, which is required by IWL5300 at the receivers (ANs) to extract the CSI information [8].

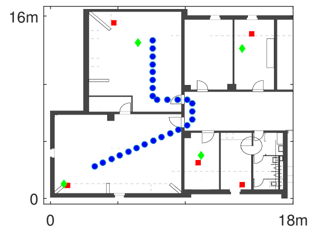
Because most of the WiFi cards in smart phones (including vendors like Apple, Samsung, Nokia, and HTC) do not support monitoring mode, a smart phone has to transfer the timestamped IMU values to a laptop (via USB), which then transmits the WiFi packet using its on-board IWL5300 WiFi card. In the smart phone, the sampling rate of the compass and accelerometer are 100Hz. As soon as the smart phone reads a pair of values from compass and accelerometer, it will forward these values together with their timestamps to the laptop over a USB cable by a Java application. The laptop will prepare the WiFi packet, whose payload includes the values of compass and accelerometer and their timestamps, and broadcast over the IWL5300 WiFi card using monitoring mode. The WiFi packet rate is also 100Hz.



(a) The First Path



(b) The Second Path



(c) The Third Path

Figure 6: Tracking in Different Paths
(Diamond Points: ANs in Scenario 1; Rectangular Points: ANs in Scenario 2; Circle Points: Ground Truth Positions)

6.2 Anchor Nodes

Anchor nodes are distributed over the area of interest to capture the packets from the target. To reduce the cost, we adopt ASUS EeeBox PCs (ePC) as ANs. First, we need to replace the original WiFi card in each ePC by an IWL5300 card, which is configured in monitoring mode. Second, after receiving a WiFi packet, each ePC needs to read the timestamp and IMU information from the payload and extract CSI information. Because the IWL5300 card supports three antennas, we read CSI from all the three antennas. Finally, all these information from all ANs are forwarded to the central server over Ethernet by sockets.

6.3 Server

A desktop PC equipped with a 4-core 3.30GHz i5 CPU is used as the server to collect the information from ANs and run offline tracking algorithms to analyze the moving trace of the target based on MATLAB. For the tracking algorithms, we first need to estimate the range and velocity information based on the algorithms introduced in subsections 5.1 and 5.2 respectively. Since we can get CSI from three antennas in one AN, we calculate the mean value of the estimated ranges from these three antennas as the input range to the particle filter from this AN. Finally, the range and velocity information will be fused in our proposed particle filter (FW-PF) to track the target. Algorithm 1 indicates the procedures of FW-PF.

Algorithm 1: FW-PF

1 Initialize filter
(I) Initial particles: $\mathbf{x}_0^i = q(\mathbf{x}_0), i = 1, \ldots, N_s$;
(II) Initial weights: $w_0^i = \frac{1}{N_s}$;
2 Update the particles: $\mathbf{x}_k^i = \mathbf{F} \cdot \mathbf{x}_{k-1}^i + \boldsymbol{\eta}\mathbf{w}$;
3 Calculate the exponential weights: $m_j = \frac{1/d_j}{\sum_{n=1}^{N} 1/d_n}$;
4 Calculate the individual likelihood:

$$p(d_j|\mathbf{x}_k^i) = \frac{1}{\sigma_j\sqrt{2\pi}} e^{-\frac{[d_j - \sqrt{(x^i - x_j)^2 + (y^i - y_j)^2}]^2}{2\sigma_j^2}};$$

5 Calculate the velocity likelihood:

$$p(\mathbf{v}_k|\mathbf{x}_k^i) = p\frac{1}{\sigma_v\sqrt{2\pi}} \text{exp}[-\frac{(\hat{v}_{x,k} - v_{x,k}^i)^2 + (\hat{v}_{y,k} - v_{y,k}^i)^2}{2\sigma_v^2}].$$

6 Update the unnormalized weights:

$$\hat{w}_k^i = p(\mathbf{v}_k|\mathbf{x}_k^i) \cdot \Pi_{j=1}^{N} p(d_j|\mathbf{x}_k^i)^{m_j};$$

7 Normalize the weights: $w_k^i = \hat{w}_k^i / \sum_{n=1}^{N_s} \hat{w}_n^i$;
8 Calculate N_{eff}: $N_{\text{eff}} = \frac{1}{\sum_{i=1}^{N_s} (w_k^i)^2}$;
9 **if** $N_{\textit{eff}} < 0.5 * N_s$ **then**
10 Resample the particles based on systematic resampling method;
11 Compute the estimated state: $\mathbf{x}_k = \sum_{i=1}^{N_s} w_k^i \mathbf{x}_k^i$;
12 Go back to step 2 for the next iteration.

7 Performance Evaluation

To evaluate the tracking accuracy of our proposed system, we have conducted a set of comprehensive measurements in a complex indoor environment.

7.1 Measurement Setup

We have evaluated our system in two scenarios on the third floor of the INF building at University of Bern. Four ANs are deployed in the first scenario (green and diamond points) and five ANs in the second scenario (red and rectangular points) as shown in Figure 6. In each scenario, the target (laptop and smartphone) is held by a person moving along three different paths (Figure 6) and experiments along each path are repeated five times. The moving speed is around $0.9m/s$ for scenario 1 and $0.6m/s$ for scenario 2. Along these moving paths, the point accuracy, which is the error from the estimated position to the ground truth position, is calculated every second. Three algorithms are evaluated along these moving paths, i.e., PDR (Pedestrian Dead Reckoning), R-PF (Ranging-only Particle Filter), FW-PF (our proposed Particle Filter with data Fusion and Weighted likelihood).

7.2 Experiment Results

Figure 7 shows CDF (Cumulative Distribution Function) of positioning errors for the three algorithms in scenario 1 (4 ANs) and scenario 2 (5 ANs). Since the performance of PDR is not related to the number of ANs, the CDF curve of PDR positioning errors summarizes all the experiments in both scenarios. Table 1 summarizes the mean error, standard deviation and 90% accuracy. Based on these results, we can find the following observations.

Table 1: Mean Errors and Standard Deviation

Tracking Methods	Mean Error	Standard Deviation	90% Accuracy
FW-PF (5ANs)	1.3m	0.7m	2.2m
FW-PF (4ANs)	1.6m	0.9m	2.8m
R-PF (5ANs)	1.7m	1.5m	3m
R-PF (4ANs)	1.8m	1.0m	3m
PDR	1.6m	2.5m	4m

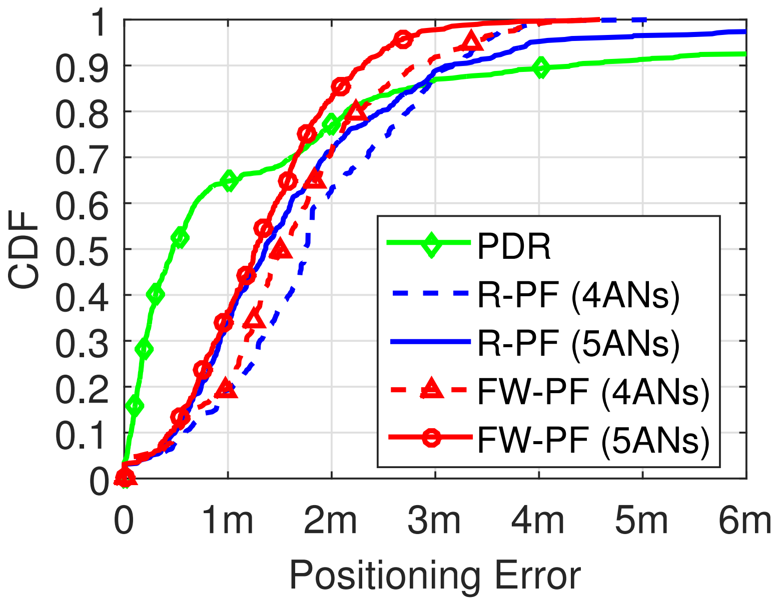


Figure 7: CDF of Positioning Errors

First, our proposed FW-PF can achieve higher accuracy and more stable performance compared to PDR. It is commonly known that PDR is prone to accumulated errors because it estimates the current location of the target by integrating the relative movement from the previous locations. Because of the accumulative errors, it is very accurate at the beginning of the moving paths by using PDR but the positioning error will increase along the moving paths. Therefore, for 50% accuracy, PDR can achieve around $0.5m$ but the accuracy severely deteriorates to around $4m$ considering 90% accuracy. In our proposed FW-PF, besides the moving velocity, which can provide the relative moving information between two sequential time intervals, the range information is considered in the likelihood function, which can provide additional information to calculate the absolute position in the local coordinate system. By considering the range information, our proposed FW-PF is more robust to accumulative errors and it achieves around $2.2m$ for 90% accuracy, which outperforms PDR by 45%. The mean error is $1.3m$, which is 19% better than PDR. Additionally, FW-PF is more stable than PDR because the standard deviation of FW-PF is $0.7m$, which is 72% smaller than PDR.

Second, our proposed FW-PF outperforms R-PF for accuracy and stability. For ranging only particle filter (R-PF), the velocity information is not considered in the likelihood function and the corresponding associated weight

update. Therefore, some particles with unusual large moving speeds could be assigned large values of associated weights. For our proposed FW-PF, the estimated velocity based on inertial sensors is considered in the likelihood function. The particles with large shift velocity components from the estimated velocity will be assigned small values of associated weights. Hence, their contributions to the final estimation are suppressed. Furthermore, by considering the exponential weights on the ranges from different ANs, the influence of ranging errors on the likelihood function is further mitigated. Therefore, our proposed FW-PF outperforms R-PF by around $0.8m$ for the 90% accuracy with 5 ANs and $0.2m$ with 4 ANs. Furthermore, the standard deviation of FW-PF is smaller than of R-PF in both scenarios, which means that the performance of FW-PF is more stable and estimated moving paths are more smooth compared to R-PF.
Finally, by increasing the number of ANs, FW-PF can integrate more range values in the likelihood function and has larger opportunity to have line-of-sight connection to one certain AN. Therefore, the performance of FW-PF gets improved by increasing the number of ANs. FW-PF with 5 ANs outperforms 4 ANs by 21% for the 90% accuracy and 19% for the mean accuracy.

8 Conclusions

In this work, we proposed a network-based indoor tracking system, which fuses the range and velocity information by an enhanced particle filter. Velocity information is estimated by an efficient method based on the timestamped values from accelerometer and compass. The range information is estimated by some enhanced ranging method relying on physical layer channel state information from WiFi signals. The enhanced particle filter (FW-PF) is adopted to fuse these two types of information in the likelihood function and is equipped with a weighting technique to mitigate the influence of ranging errors. The system is implemented by using some cheap commercial devices for ANs, which are able to extract the inertial sensor information and CSI information from the received WiFi packets. We evaluated our proposed system in a complex indoor environment. Evaluation results indicate that our proposed FW-PF is more accurate and stable than pedestrian dead reckoning and range-only particle filters. The mean accuracy achieves $1.3m$ and 90% accuracy is $2.2m$.

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