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Passively Track WiFi Users with an Enhanced Particle Filter using Power-based Ranging

Zan Li, Torsten Braun

Technischer Bericht INF-15-005 vom 22. December 2015

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Abstract

Passive positioning systems produce user location information for third-party providers of positioning services. Since the tracked wireless devices do not participate in the positioning process, passive positioning can only rely on simple, measurable radio signal parameters, such as *timing* or *power* information. In this work, we provide a passive tracking system for WiFi signals with an enhanced particle filter using fine-grained power-based ranging. Our proposed particle filter provides an improved likelihood function on observation parameters and is equipped with a modified coordinated turn model to address the challenges in a passive positioning system. The anchor nodes for WiFi signal sniffing and target positioning use software defined radio techniques to extract channel state information to mitigate multipath effects. By combining the enhanced particle filter and a set of enhanced ranging methods, our system can track mobile targets with an accuracy of $1.5m$ for 50% and $2.3m$ for 90% in a complex indoor environment. Our proposed particle filter significantly outperforms the typical bootstrap particle filter, extended Kalman filter and trilateration algorithms.

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1 Introduction

In recent years, research on radio-based indoor positioning has become increasingly important, motivated by the shortcomings of the Global Positioning System (GPS) indoors. Wireless technologies are ideal candidates for indoor positioning, due to their ubiquitousness. Particularly, WiFi (IEEE 802.11) is currently the dominant local wireless network standard for short-range communication in indoor environments and is the leading technology for radio-based indoor positioning [1]. To locate WiFi devices, several positioning algorithms have been proposed, which can be classified as range-based and range-free. Range is defined as the propagation distance between the target and an Anchor Node (AN). Range-based positioning techniques need to calculate the range information from certain measured radio parameters, e.g., timing and power information. After obtaining range information, the location of the target can be estimated based on the known coordinates of ANs. Instead of calculating range information, fingerprinting, which is a commonly used range-free technique, requires a radio map to locate users. Although fingerprinting can achieve satisfying positioning accuracy, it is very labour intensive to build up the radio map.

Irrespective of the positioning algorithms, indoor positioning systems can be classified as active and passive positioning systems based on the target's participation. In an active positioning system, target devices need to actively participate in the positioning process. For example, active positioning based on smart phones can leverage inertial sensors to estimate the moving state of the target and achieve high tracking accuracy [2]. In a passive positioning system, the target devices are oblivious to the positioning process. Instead, several signal sniffers are deployed as ANs to passively overhear the packets from tracked devices. A server collects the useful information (e.g., timing and power information) from different ANs and run positioning algorithms [1].

Passive positioning systems for WiFi users are attractive for third-party providers of positioning and monitoring services. For example, shop owners can analyze their customers' buying behaviour based on their location information. However, to design passive positioning systems for mobile targets, one of the critical challenges is the limited information for positioning. Since ANs only overhear signals, the ranging schemes can only rely on simple radio signal parameters measured at ANs, such as *timing* and *power* information. Converting this basic information into the dynamic locations of a mobile target involves a sequence of steps, each of which may introduce errors. The foremost goal of our work is to minimize the errors

as much as possible and passively track the mobile WiFi users with high accuracy and low labour effort.

In this work, we provide a positioning system relying on software defined radio techniques to passively capture signals from WiFi users and extract channel information for accurate indoor tracking. In the system, we design an enhanced particle filter exclusively relying on fine-grained power-based ranging, in which the initial training effort is significantly less than fingerprinting. Our main scientific contributions are summarized as follows.

First, we propose an enhanced particle filter for indoor tracking by improving the likelihood function on the observation parameters and introducing a modified coordinated turn moving model. For particle filters, we have three main scientific contributions. First, instead of using a constant velocity moving model as in most indoor tracking works, we propose a modified coordinated turn model, which considers the angle variation of the moving direction in the movement state and provides higher tracking accuracy for a passive tracking system. Second, we investigate the impact of ranging errors on the likelihood function in the particle filter and the relation between ranging outputs and ranging errors. By weighting the likelihoods for different ANs based on their ranging outputs, our particle filter significantly mitigates the influence of ranging errors. Third, in a passive positioning system, speed information is normally unavailable to the tracking process because the system can not get the inertial sensor information from the target. In our system, we consider the moving speed limitation on the likelihood by filtering out the uncommonly large moving speed for people in indoor environments.

Second, a collection of methods to improve ranging accuracy are adopted in the system, specifically targeting the mitigation of multipath propagation and the more accurate propagation model. To mitigate multipath propagation, we work on Channel Impulse Response (CIR) to extract the fine-grained power from the Line Of Sight (LOS) path [1]. To extract the CIR information from the passive WiFi signal sniffers, software defined radio techniques allow us to decode the WiFi signals from the physical layer and extract channel information from the decoded packets. Furthermore, we smooth the fine-grained power by a Savitzky-Golay (S-G) filter [3], which considers the trend of power changes in the moving window. Further, instead of using the typical Log-Distance-Path-Loss (LDPL) propagation model, we model the relation between measured power information and ranges as a non-linear curve fitting problem and solve this problem using a Non-Linear Regression (NLR) model.

Finally, besides our proposed tracking mechanism, we also implement a collection of commonly used positioning mechanisms, i.e., Bootstrap Parti-

cle Filter (BPF), Extended Kalman Filter (EKF), Trilateration with Maximum Likelihood (ML), Linear Least Square (LLS), and an enhanced weighted least square algorithm proposed in our previous work [1]. We provide a deep experimental evaluation and comparison of those positioning mechanisms along different moving paths in a complex indoor environment. In the remainder of the paper, related works are reviewed in Section 2. Some preliminaries for particle filters and a general form of the range-based particle filter are introduced in Section 3. In this section, the problems in a passive tracking system are particularly stated. Our main contributions are introduced in Section 4, in which the proposed enhanced particle filter is described. The ranging mechanisms are presented in Section 5. Section 6 presents the implementation of the proposed algorithms in a passive SDR-based positioning system for WiFi signals. Section 7 presents the evaluation results in a complex indoor environment. Finally, Section 8 concludes the paper.

2 Related Work

Passive positioning of mobile targets is typically more challenging than active positioning because it can only collect limited information, i.e., radio parameters at the AN side.

Inertial sensors have been intensively investigated in the area of active indoor tracking due to the 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 with high accuracy. The authors of [4] provided a system called Zee, which adopts the inertial sensors and crowdsourcing to achieve a calibration free WiFi-based positioning system. The authors of [2] proposed the Wap tracking system, in which a particle filter is used to fuse the inertial sensor information and Received Signals Strength Indicator (RSSI) of WiFi signals to track the smart phone itself. In those works, inertial sensors play an important role to achieve accurate indoor tracking. However, passive positioning systems can not gain from inertial sensors due to the lack of user participation.

Time-based positioning for WiFi users is still considered to be challenging due the limited accuracy of timestamps and imperfect synchronization. Round Trip Time (RTT) as a synchronization-free mechanism has been recently proposed for passive WiFi positioning. However, limited by the bandwidth of WiFi (20MHz), the 80% accuracy can only achieve 3.7 – 5.8m as reported in [5]. For passive indoor positioning, time-based localization is even more challenging because ANs should be perfectly synchronized with each other [6].

Power information is an efficient and low cost solution for a passive positioning system. RSSI is the most commonly used parameter, which can be directly taken from most commercial WiFi cards. However, it is normally error-prone to severe multipath influence and measurement errors. To achieve accurate positioning, RSSI-based fingerprinting has been developed for decades. RADAR [7] and Horus [8] are two well known fingerprinting systems, which require to build a radio map before online locating the target. Bayesian filters have been investigated [9, 10] based on fingerprinting algorithms to track users. Although fingerprinting can provide satisfying positioning accuracy, it is very labour intensive to build the radio map. In contrast to fingerprinting, range-based positioning algorithms require less labour effort to calibrate the system but are prone to inaccurate ranging models and multipath effects. The LDPL model is typically

adopted to map RSS into propagation distance d [11, 12]:

$$\text{RSS} = P_t - (\text{PL}(d_0) + 10 \cdot \gamma \cdot \log_{10}(\frac{d}{d_0}) + X_\theta), \quad (1)$$

where P_t is the transmission power in dBm, $\text{PL}(d_0)$ is the path loss at reference point d_0 and γ is the path loss exponent. X_θ is a zero-mean normal random variable reflecting shadowing attenuation in dB. Because shadowing attenuation is a random variable and challenging to be modeled in different environments, Non-Line-Of-Sight (NLOS) propagation usually introduces large ranging errors to the ranging estimation based on the LDPL model. In addition, multipath propagation will introduce some constructive and destructive interference to RSS, which makes high accurate ranging with the LDPL model more challenging. After ranging, positioning algorithms are used to estimate the location of the target based on the propagation distances to different ANs. Several researchers have investigated trilateration algorithms including LLS and ML based on RSSI-based ranging, such as [13] [14]. The authors of [15] experimentally evaluated Kalman filters using RSSI-based ranging. We found few works to investigate particle filters exclusively using power-based ranging for indoor positioning. The authors of [16] investigated particle filters using RSSI-based ranging in an outdoor environment but their results showed an accuracy of $4m$ to $6m$, which is not accurate enough for indoor tracking.

Channel information can be considered as a fine-grained power information and has been first proposed by the authors of [17] in a prototype called FILA, in which channel information is investigated to estimate the ranging information and a simple trilateration algorithm with LLS is further adopted to locate the target. FILA has demonstrated that channel 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 (IWL 5300) to extract Channel State Information (CSI) based on an improved firmware [18]. However, the firmware does not support to extract CSI from overheard packets. Hence, this network card with the firmware can not be used for a passive localization system. In our work, we propose a passive indoor positioning system, which can extract channel information from the overheard packets based on software defined radio techniques. In [1], we proposed an enhanced trilateration algorithm based on channel information, which combines Weighted Centroid and Constrained Weighted Least Square (WC-CWLS). The algorithm outperforms LLS for static targets. Although we evaluated our proposed trilateration algorithm for mobile targets in [1], we did not consider the Bayesian estimation methods, i.e., Kalman filter and particle filter,

which are more accurate to track mobile targets.

3 Problem Definition and Preliminaries

We consider the problem of tracking the location (coordinates) of a mobile wireless device over time and in two-dimensional space, given a stream of noisy RSS measurements from at least three ANs, that can passively overhear the device's transmissions. Thus, at time k , we have:

- an unknown system state vector \mathbf{x}_k including the target's location (or velocity and accelerated velocity in addition),
- a discrete sequence of noisy measurement vectors $\mathbf{z}_{1:k}$, taken at times $1, \dots, k$ including the distances to the different ANs, obtained from the RSS information.

The target moves according to a non-linear function:

$$\mathbf{x}_k = \mathbf{f}_k(\mathbf{x}_{k-1}, \mathbf{v}_k), \quad \text{(system model)}$$

and the measurement system observes the target according to another non-linear function:

$$\mathbf{z}_k = \mathbf{h}_k(\mathbf{x}_k, \mathbf{u}_k), \quad \text{(observation model)}$$

where \mathbf{v}_k and \mathbf{u}_k are the system and measurement noise, respectively.

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 Density Function (PDF) $p(\mathbf{x}_0)$ [19]. This degree of belief is the posterior PDF over the state space of our system.

Both Kalman filter and Extended Kalman Filter assume that the noises in the above functions as well as the posterior PDF are Gaussian. As a result, a recursive propagation of estimates of the first two moments produces an optimal estimation method for Gaussian processes. 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:

$$p(\mathbf{x}_k | \mathbf{z}_{1:k}) \approx \sum_{i=1}^{N_s} w_k^i \delta(\mathbf{x}_k - \mathbf{x}_k^i), \quad (2)$$

where \mathbf{x}_k^i is the i th particle and w_k^i is the *associated weight*. N_s is the total number of particles. Using the principle of *importance sampling*, as

described in [19], the associated weights can be calculated as:

$$w_k^i \propto w_{k-1}^i \cdot \frac{p(\mathbf{z}_k | \mathbf{x}_k^i) p(\mathbf{x}_k^i | \mathbf{x}_{k-1}^i)}{q(\mathbf{x}_k^i | \mathbf{x}_{k-1}^i, \mathbf{z}_k)}, \quad (3)$$

where $p(\mathbf{z}_k | \mathbf{x}_k^i)$ is the measurement *likelihood* of \mathbf{z}_k conditioned on \mathbf{x}_k^i , $p(\mathbf{x}_k^i | \mathbf{x}_{k-1}^i)$ is the *transition density* from state \mathbf{x}_{k-1}^i to \mathbf{x}_k^i , and $q(\mathbf{x}_k^i | \mathbf{x}_{k-1}^i, \mathbf{z}_k)$ is the *importance density*. The importance density must be designed such that samples of it are easy to generate.

3.1 Range-based Bootstrap Particle Filter for Passive Tracking

One of the most widely used and efficiently implementable particle filter is Bootstrap Particle Filter (BPF) [20], in which the importance density is chosen to be equal to the transition density:

$$q(\mathbf{x}_k | \mathbf{x}_{k-1}, \mathbf{z}_k) = p(\mathbf{x}_k | \mathbf{x}_{k-1}). \quad (4)$$

Hence, the associated weights can be calculated as:

$$w_k^i \propto w_{k-1}^i \cdot p(\mathbf{z}_k | \mathbf{x}_k^i), \quad (5)$$

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

An efficient and accurate derivation of the likelihood function $p(\mathbf{z}_k | \mathbf{x}_k^i)$ is essential for accurate tracking by BPF. For range-based tracking, \mathbf{z}_k comprises range information from different ANs, i.e., $\mathbf{z}_k = [d_1, d_2, \dots, d_N]$, where d_j is the range between the target and the j th AN. Assuming that the range information from different ANs are independent from each other, a typical likelihood can be written as

$$p(\mathbf{z}_k | \mathbf{x}_k^i) = \prod_{j=1}^N p(d_j | \mathbf{x}_k^i). \quad (6)$$

In order to distinguish these two likelihoods, we refer to $p(\mathbf{z}_k | \mathbf{x}_k^i)$ as the *whole likelihood* and $p(d_j | \mathbf{x}_k^i)$ as the *individual likelihood* in the remainder of this paper.

In addition, due to lack of information about moving velocity, a Constant Velocity (CV) model is commonly used as the system model for a passive tracking system. In this model, the state vector is defined as,

$$\mathbf{x} = [x, y, \hat{x}, \hat{y}]^T, \quad (7)$$

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

$$\mathbf{x}_k = \mathbf{F} \cdot \mathbf{x}_{k-1} + \boldsymbol{\eta} \mathbf{w}, \quad (8)$$

where

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

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 the remainder of this paper, the bootstrap particle filter with CV system model as in Equation (8) and the likelihood as in Equation (6) is referred to as the traditional BPF.

3.2 Problem Statement

In order to achieve high tracking accuracy exclusively relying on power-based ranging, we will address the following three problems in BPF particularly for passive power-based indoor tracking.

First, the velocity components (\hat{x}, \hat{y}) on the x and y axes are updated and treated independently in the CV moving model, which does not consider the relation between the two components. Actually, the two velocity components on the x and y axes can be related by the angle variation of the target's moving direction, especially when the target changes its moving direction.

Second, different from time-based localization with specific signals, which benefits from high ranging accuracy, power-based positioning normally suffers from large ranging errors. Because of the large ranging errors, \mathbf{z}_k is normally shifted from the real value, \mathbf{z}'_k , which makes the whole likelihood $p(\mathbf{z}_k | \mathbf{x}_k^i)$ biased from the real whole likelihood, $p(\mathbf{z}'_k | \mathbf{x}_k^i)$. Correspondingly, the associated weights will be inaccurately updated, which results in inaccurate location estimation.

Finally, in BPF, only ranging information is considered in the likelihood estimation but velocity information is normally neglected due to lack of velocity information. However, due to the inaccurate ranging information and the lack of velocity observation information in the observation model to correct the predicted velocity from the system model, the predicted velocity in the

state \mathbf{x}_k can get very large, which is unusual for people moving in indoor environments and introduces large tracking errors.

4 An Enhanced Range-only Particle Filter

As introduced in Section 3, the accuracy of indoor tracking based on particle filter can be deteriorated due to inaccurate likelihood and motion model. In this section, we will propose an enhanced particle filter to address these three problems in a traditional BPF as mentioned in Section 3.2.

4.1 Modified Coordinated Turn Model

The motivation of tracking algorithms is to provide a robust method to track randomly moving targets, e.g., changing moving direction. A coordinated turn model has been proposed in some previous research on bearings only tracking [21] and time-based ranging only tracking [22]. In both works, the coordinated turn model is divided into three switching dynamic models including CV models and two coordinated turning models. A regime is required to switch between different models.

In this work, we propose a Modified Coordinated Turn (MCT) model, in which instead of estimating the moving models, an angle variation parameter is estimated in the system state and the regime as in [21] is not required to switch between different models. In our model, the state vector is defined by,

$$\mathbf{x}' = [x, y, \hat{x}, \hat{y}, \theta]^T, \quad (9)$$

where θ indicates the angle variation of the moving direction. Considering the relation between the two-dimensional moving speed vector (\hat{x}, \hat{y}) and θ , the MCT model can be defined as

$$\mathbf{F}_{\text{MCT}} = \begin{pmatrix} 1 & 0 & \sin(\Delta T\theta)/\theta & (\cos(\Delta T\theta) - 1)/\theta & 0 \\ 0 & 1 & (1 - \cos(\Delta T\theta))/\theta & \sin(\Delta T\theta)/\theta & 0 \\ 0 & 0 & \cos(\Delta T\theta) & -\sin(\Delta T\theta) & 0 \\ 0 & 0 & \sin(\Delta T\theta) & \cos(\Delta T\theta) & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix}. \quad (10)$$

By introducing the angle variation of moving direction θ , the particle filter can more smoothly track the targets, especially when the target suddenly changes its moving directions. In the remainder of this paper, BPF equipped with the modified coordinated Turn model is referred to as T-BPF.

4.2 Weighted Likelihood based on Ranging Information

Since power-based ranging normally faces large ranging errors, we propose to provide a modified BPF, whose performance should be robust to ranging errors.

As mentioned in Section 3, range estimation is often biased and correspondingly the individual likelihoods $p(d_j|\mathbf{x}_k^i)$ from different ANs are often biased from the real individual likelihoods $p(d'_j|\mathbf{x}_k^i)$, where d'_j is the ground truth propagation distance. Furthermore, depending on the locations of ANs, the ranges estimated by different ANs normally face different ranging errors. Especially in a complex indoor environment with mixed LOS and NLOS conditions, LOS and NLOS ranging are often substantially different. However, a typical BPF just simply treats all the individual likelihoods from different ANs equally as in Equation (6). This oversimplification introduces large estimation errors, because in a multiplication form of the individual likelihoods as in Equation (6), the inaccurate individual likelihoods $p(d_j|\mathbf{x}_k^i)$ from certain ANs with large ranging errors will significantly affect the accuracy of the whole likelihood estimation $p(\mathbf{z}_k|\mathbf{x}_k^i)$.

Therefore, to mitigate the influence of the large ranging errors on the estimation of the whole likelihood $p(\mathbf{z}_k|\mathbf{x}_k^i)$, we propose to adopt a weighting technique on the whole likelihood $p(\mathbf{z}_k|\mathbf{x}_k^i)$ estimation by suppressing the emphasis on the individual likelihoods $p(d_j|\mathbf{x}_k^i)$ 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 (W-BPF) with exponential weights on each individual likelihood from different ANs as

$$p(\mathbf{z}_k|\mathbf{x}_k^i) = \prod_{j=1}^N p(d_j|\mathbf{x}_k^i)^{m_j}, \quad (11)$$

where m_j is the *exponential weight* for the individual likelihood of the j th 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. Figure 1 indicates the relation between the ranging outputs and their corresponding ranging errors based on a set of measurements in our institute building, which provides a complex indoor environment under mixed LOS and NLOS conditions. In general, we can find that the range errors increase with the estimated range values. Therefore, instead of relying on the ranging errors, we can use the estimated

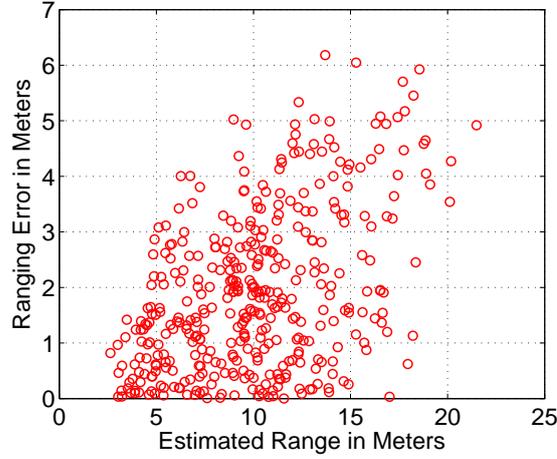


Figure 1: Ranging Error vs. Estimated Range

ranging outputs to infer their corresponding errors and set the exponential weights to be inversely proportional to the estimated range outputs as

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

which are normalized by $\sum_{j=1}^N m_j = 1$. With the proposed W-BPF method, we expect to mitigate the influence of ranging errors, especially for NLOS propagation, whose ranging errors are normally larger than for LOS conditions.

4.3 Moving Velocity Limitation on Likelihood

Since the state of the system, \mathbf{x}_k , includes the moving velocity of the target, we propose to further introduce a velocity related parameter γ to the whole likelihood estimation. The whole likelihood as in Equation (11) can be rewritten as,

$$p(\mathbf{z}_k | \mathbf{x}_k^i) = \gamma_k \cdot \prod_{j=1}^N p(d_j | \mathbf{x}_k^i)^{m_j}. \quad (13)$$

As mentioned before, in an active positioning system, the velocity related parameter γ can be determined by the output of inertial sensors. For example, accelerometer sensors can be used to estimate the absolute value of moving velocity. In passive positioning systems, this information is unavailable to the tracking system and hence the likelihood of velocity is typically ignored. Furthermore, because of inaccurate ranging, the location estimation between two consequent sampling intervals can be far

away from each other, which results in large estimated moving velocity. However, this fast moving velocity is typically impossible in indoor environments, e.g., offices and shopping malls.

Therefore, in our work, instead of estimating the moving speed by some inertial sensors, we consider the limitation on the moving speed of people in an indoor environment, where walking is normally considered as the usual case. Some studies have been done to investigate the walking speed of people. As reported in [23], the maximum gait speed is limited to around $2.5m/s$. Therefore, we configure the velocity related parameter γ as,

$$\begin{cases} \gamma = 1, & 0 < |v| < 3m/s; \\ \gamma = 4 - |v|, & 3m/s < |v| < 4m/s; \\ \gamma = 0, & 4m/s < |v|, \end{cases} \quad (14)$$

where $|v| = \sqrt{v_x^2 + v_y^2}$ is the absolute value of the estimated velocity in each particle. In an office environment, people may sit at their working place or walk between offices. Therefore, we set the velocity related parameter γ as 1 when the moving velocity is smaller than $3m/s$, which is $0.5m/s$ larger than the maximum gait speed in [23]. If the velocity is larger than $3m/s$ but smaller than $4m/s$, γ will linearly decrease from 1 to 0. If the velocity is larger than $4m/s$ that does not frequently happen in an office environment, γ will be set to 0.

Based on this velocity related parameter γ , we expect that the particles with uncommon moving velocity will be filtered out and hence the estimated moving trace will be smoothed. BPF only considering the velocity limited on the likelihood is referred to as V-BPF in the remainder of the paper. BPF equipped with the MCT model (Equation (10)) and adopting the modified likelihood (Equation (13) including γ and exponential weights) is referred to as WVT-BPF.

5 Power-based Ranging with High Accuracy

As introduced in Section 3, the main reason for large tracking errors using power-based ranging is inaccurate ranging. More accurate estimation of \mathbf{z}_k is a prerequisite to improve the tracking accuracy by particle filter. This section will present our solutions for accurate ranging [1].

5.1 Multipath Mitigation via CIR

Channel information can be classified as Channel State Information (CSI) in the frequency domain and Channel Impulse Response (CIR) in the time domain. CSI reveals a set of channel measurements depicting the amplitudes and phases of every subcarrier in the frequency domain. CIR characterizes the individual paths of the communication channel in the time domain as a set of temporal linear filters [24]. CSI in the frequency domain can be converted into CIR in the time domain via Inverse Fast Fourier Transform (IFFT). In the time domain, CIR can be modeled as

$$h(\tau) = \sum_{n=1}^N a_n e^{-j\theta_n} \delta(\tau - \tau_n) \quad (15)$$

where a_n , θ_n and τ_n are the amplitude, phase and time delay of the n th path. N is the total number of paths and $\delta(\tau)$ is the Dirac delta function. The bandwidth of IEEE 802.11n is 20MHz and hence the time resolution of an estimated CIR is $1/20\text{MHz} = 50\text{ns}$, i.e., $\tau_n - \tau_{n-1} = 50\text{ns}$. Therefore, the measured CIR is a digitalized channel, which can only distinguish several clusters of propagation paths rather than every individual multipath component [17, 25].

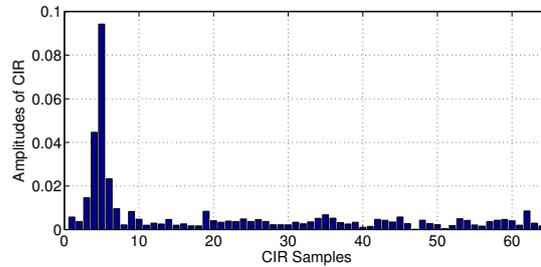


Figure 2: Channel Impulse Response

Figure 2 indicates the amplitudes of the measured CIR in our testbed with LOS connection between the target and a SDR-based receiver. As shown in the figure, there is a path with strongest power in the CIR samples and the amplitudes in the other channels are much smaller. It is commonly known that the signal from the LOS propagation path should have the strongest power and the others are from multipath propagation. However, there is an uncertain delay at the start of measured CIR samples, because of the low time resolution and inaccurate synchronization to detect the beginning of the long preambles [26]. Hence, to mitigate the influence of multipath propagation, the path with the maximal power can be selected as the LOS path and the power in this path can be chosen as the estimated power. The final estimated power is as

$$RSS = 10 \cdot \log_{10}[\max(|h(\tau)|)^2] \quad (16)$$

where $|h(\tau)|$ indicates the amplitudes of CIR over 64 samples. In case that no LOS path exist, we can still select the shortest NLOS propagation paths with the strongest power.

5.2 Multipath Mitigation via the S-G Filter

In contrast with locating a static user, the mobile target will face different multipath effects in different locations along his moving path, which will result in large variation in the measured power. Typically, we can adopt a smooth filter to smooth the measured power and mitigate the multipath effect. In this work, we propose to adopt a S-G filter to smooth the measured power. The S-G filter applies a moving window smoothing technique based on least squares polynomial fitting [27], which has the advantage of preserving the original shape and features of the signal, e.g., the trend of RSS changes in the moving window. We take the group of $2M + 1$ RSS samples centred at n , which is moving from 0 to the end of the samples. The RSS values can be estimated as a polynomial with the coefficients $[a_0, a_1, \dots, a_{N_p}]$,

$$RSS'_{SG}(n) = \sum_{i=0}^{N_p} a_i n^i. \quad (17)$$

To obtain the coefficients, we minimize the mean-squared approximation error as

$$\operatorname{argmin}_{[a_0, a_1, \dots, a_{N_p}]} \sum_{j=n-M}^{n+M} \left(\sum_{i=0}^{N_p} a_i j^i - RSS(j) \right)^2, \quad (18)$$

where N_p is the order of polynomial. $RSS'_{SG}(n)$ is a smoothed version of the raw RSS values by the S-G filter.

5.3 Non-linear Regression Model

For range-based localization algorithms, the measurement parameters, e.g., RSS, should be converted into propagation distances based on a certain model. The LDPL model as Equation (1) is a generic model to predict the path loss for a wide range of environments. However, the LDPL model has been demonstrated to be inaccurate for indoor environments. A typical method to obtain the LDPL model is based on linear regression [11, 12], which models the relationship between the RSS values and logarithmic propagation distances as a linear function as shown in Figure 3(a).

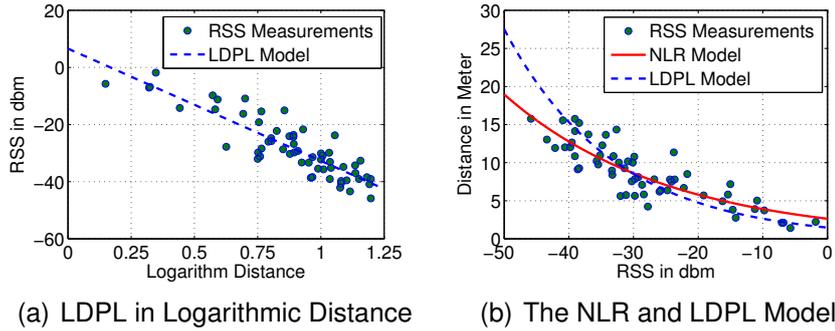


Figure 3: The LDPL and NLR Models

In our work, we propose to model the relationship between the RSS values and propagation distances as a nonlinear curve fitting problem. Hence, we provide a nonlinear regression (NLR) model as,

$$\hat{d}_i = \alpha_i \cdot e^{\beta_i \cdot RSS_i} \quad (19)$$

where \hat{d}_i is the distance between the target and i th AN, RSS_i is the RSS values obtained at the i th AN, α_i and β_i are two unknown parameters in the model that need to be obtained from some initial measurements. Depending the layout of the test environment and locations of ANs, different ANs normally face different propagation channels. Therefore, we adapt different (α, β) pairs for different ANs to match different propagation channels.

Given K training positions in the initial measurements, $(d_{ij}, \text{RSS}_{ij})$ are collected at the j th training position from the i th AN. We apply the nonlinear least square criterion, in which the sum of squared residuals should be minimized as,

$$\underset{(\alpha_i, \beta_i)}{\operatorname{argmin}} \sum_{j=1}^K (\alpha_i \cdot e^{\beta_i \cdot \text{RSS}_{ij}} - d_{ij})^2. \quad (20)$$

To find the solution of this unconstrained optimization problem, the trust region algorithm [27] is applied in our work, because it is robust and has strong global convergence properties. The red solid curve in Figure 3(b) indicates the NLR model to fit the RSS measurements and the ground truth distances.

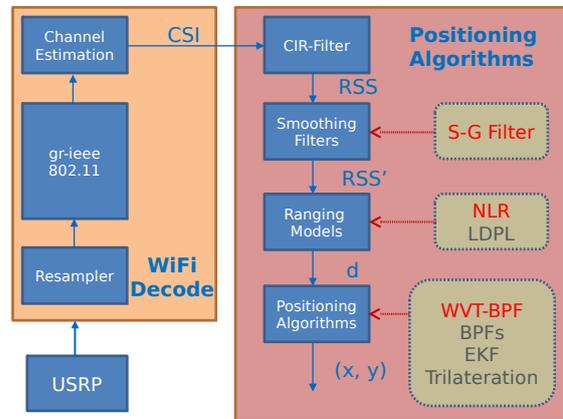


Figure 4: Testbed Structure

6 Implementation of WiFi Tracking in a Passive SDR-based Testbed

Our proposed tracking algorithms have been implemented in a software defined radio based passive positioning system for WiFi devices. Figure 4 indicates the structure of this testbed. Basically, the testbed can be divided into three main components: receiving hardware for WiFi signals, WiFi packet decoding, and positioning algorithms.

6.1 Receiving Hardware for WiFi Signals

As mentioned in Section 2, off-the-shelf network cards (IWL 5300) with firmware [18] can not be adopted for a passive localization system to extract the channel information in ANs. Hence, to decode IEEE 802.11n up-link messages and extract channel information, we adopt SDR techniques for ANs. These techniques realize signal processing in an open source software. In our work, the sniffing component is based on USRP N210 receivers [28], which include WBX daughter-boards for receiving and digitalizing analog signals and a FPGA in a mother-board for resampling.

6.2 WiFi Packet Decoding

Each USRP device is connected to one individual desktop, in which GNU Radio software [29] is adopted for signal processing. WiFi packet decoding

is mainly realized by the framework [30] for IEEE 802.11a/g/p decoding in GNU Radio (gr-ieee 802.11 block in Figure 4). We extract the long preambles from the decoded WiFi packets and design a channel estimation block based on MATLAB to estimate CSI in frequency domain. To meet our requirements of channel estimation and localization, we need to modify the framework (gr-ieee 802.11) as follows.

First, in order to mitigate estimation errors of CSI, the distortion of the filters in the USRP receivers in the frequency domain should be minimized. Hence, instead of 20MHz sampling rate in the framework [30], we use a 25MHz sampling rate to keep the frequency response of the filters in the USRP receivers flat in the target bandwidth. We work on the IEEE 802.11n standard with 20MHz bandwidth and therefore the frequency response of low-pass filters in the baseband should be flat within 10MHz. In the mother-board of USRP, a Cascaded Integrator Comb (CIC) filter is implemented to convert the sampling rate from 100MHz to the required rate. In the CIC filter, the downsampling rate should be set to integer multiplications of 4 to avoid the serious frequency roll-off. Figures 5(a) and 5(b) show the simulated baseband frequency response of CIC filter in the mother-board of USRP N210 with 20MHz and 25MHz sampling rates respectively. With a sampling rate of 20MHz, the filter has about 18dB attenuation at 10MHz compared to 0MHz. With a sampling rate of 25MHz, the frequency response of CIC filter is flat from 0MHz to 10MHz. Therefore, we use the sampling rate of 25MHz as the output from USRP and a resampler is adopted at the beginning of the signal processing to convert the sampling rate from 25MHz to 20MHz.

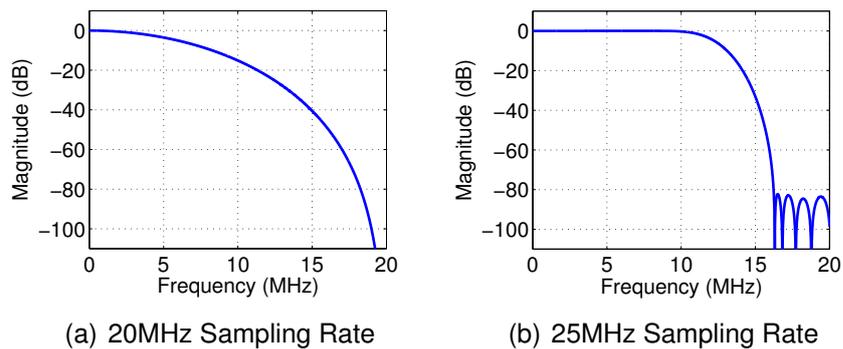


Figure 5: Baseband Frequency Response of CIC Filter with Different Sampling Rates

Second, we use Long Preambles (LP) in the decoded WiFi packets for channel estimation, which are normally used for packet synchronization

and channel estimation in WiFi receivers [31]. In the framework [30], the long preambles are detected before demodulation and the packets are reconstructed after demodulation. Therefore, to map the long preambles to their corresponding packets, we pass the long preambles to the packet reconstruction module through the whole decoding procedure. To achieve this, we adopt the stream tags mechanism [29] from GNU Radio. In addition, for passive localization and tracking, the server running localization algorithms should aggregate the RSS values of the packets from different ANs in the same time interval. Hence, the clock time in the ANs are synchronized by GPS receivers. GPS timestamps that indicate the detection time of the packets are also attached by stream tags in GNU Radio. Consequently, the server can align the packets from different ANs with GPS time and aggregate the RSS values in the same time interval from different ANs.

Third, Long preambles are attached to packets and passed to MATLAB for channel estimation. We adopt block-type pilot channel estimation based on long preambles to estimate the CSIs in 64 subcarriers. We adopt the Least Square (LS) estimator to estimate CSI in the frequency domain. CSI can be estimated as,

$$\hat{\mathbf{H}} = \underset{\mathbf{H}}{\operatorname{argmin}} (\mathbf{Y} - \bar{\mathbf{X}}\mathbf{H})^H (\mathbf{Y} - \bar{\mathbf{X}}\mathbf{H}), \quad (21)$$

where $(\cdot)^H$ indicates the conjugate transpose operation, and $\bar{\mathbf{X}}$ and \mathbf{Y} are the predefined and received long preambles in the frequency domain respectively. As derived in [24], the solution of the LS estimator is given as,

$$\hat{\mathbf{H}} = \bar{\mathbf{X}}^{-1}\mathbf{Y}. \quad (22)$$

In the frequency domain, CSI at each subcarrier can be represented as,

$$\hat{\mathbf{H}}(k) = A_k e^{-j\phi_k}, \quad (23)$$

where A_k and ϕ_k are the amplitude and phase at the k th subcarrier.

6.3 Positioning Algorithms

As shown in Figure 4, positioning algorithms are designed in a central server, which runs MATLAB to analyze the moving path of the WiFi target. Basically, the positioning related algorithms are designed in four steps. First, CSI needs to be converted to CIR in time domain by IFFT, and the power (RSS) from the direct path is estimated based on Equation (16).

Second, the RSS values will be smoothed by the S-G filter, in which the window size is set to 5 and the order of the polynomial is 3. Third, the outputs of the S-G filter will be fed into the non-linear regression model to calculate the range information from different ANs. Finally, the range information will be the input to the WVT-BPF algorithm (Algorithm 1) to track the target.

Algorithm 1: WVT-BPF

- 1 Initialize filter
 - (I) Initial particles: $\mathbf{x}_0^i = q(\mathbf{x}_0), i = 1, \dots, N_s$;
 - (II) Initial weights: $w_0^i = \frac{1}{N_s}$;
- 2 Update the particles: $\mathbf{x}_k^i = \mathbf{F}_{\text{MCT}} \cdot \mathbf{x}_{k-1}^i + \boldsymbol{\eta}\mathbf{w}$;
- 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 Update the unnormalized weights:

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

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

System Model: To passively track WiFi users, the proposed MCT model in section 4.1 is adopted in WVT-BPF. Recall that the state vector in WVT-BPF includes the Cartesian coordinates of the target (x, y) , the two-dimensional moving speed vector (\hat{x}, \hat{y}) , and the angle variation of moving direction θ , i.e., $\mathbf{x}' = [x, y, \hat{x}, \hat{y}, \theta]^T$. For each iteration, the particles are updated based on Equation (8) with \mathbf{F}_{MCT} in Equation (10).

Observation Model: The measurement vector includes ranging information from different ANs as $\mathbf{z}_k = [d_1, d_2, \dots, d_N]$. For each AN, the observa-

tion function can be defined as:

$$d_j = \sqrt{(x - x_j)^2 + (y - y_j)^2} + u_j, \quad (24)$$

where (x_j, y_j) are the coordinates of the j th AN and u_j is the Gaussian noise of the j th AN with a variance of σ_j .

Weight Update and Location Estimation: Based on Equation (24), the individual likelihood for the j th AN can be written as:

$$p(d_j | \mathbf{x}_k^i) = \frac{1}{\sigma_j \sqrt{2\pi}} e^{-\frac{[d_j - \sqrt{(x^i - x_j)^2 + (y^i - y_j)^2}]^2}{2\sigma_j^2}}, \quad (25)$$

and the whole likelihood $p(\mathbf{z}_k | \mathbf{x}_k^i)$ can be calculated based on Equation (13), which considers the exponential weights m_j and the velocity related parameter γ . Finally, we can update the associated weights based on Equation (5) and estimate the location of the target by calculating the weighted average of the particles as:

$$\mathbf{x}_k = \sum_{i=1}^{N_s} w_k^i \mathbf{x}_k^i. \quad (26)$$

Resampling: With this weighted multiplication likelihood and speed limitation, the particle filter is prone to the sample degeneracy problem, which results in serious performance degradation. To deal with the sample degeneracy problem, resampling is typically adopted [20]. A suitable measure of degeneracy is the effective sample size $N_{\text{eff}} = 1 / \sum_{i=1}^{N_s} (w_k^i)^2$. As soon as N_{eff} is smaller than $0.5 * N_s$, the degeneracy is considered to be serious and a suitable resampling method should be adopted. In our work, a systematic resampling method [20] is adopted in our work, because of its high accuracy and efficient implementation.

Algorithm 1 summarizes the procedure of WVT-BPF. Additionally, some commonly used positioning algorithms are also implemented in our system: a traditional BPF, extended Kalman filter, trilateration algorithms including ML, LLS and WC-CWLS, which is proposed in our previous work [1]. Table 1 summarizes the abbreviations of those positioning methods and ranging models.

Table 1 : Abbreviation List

	Bootstrap Particle Filter	
Positioning Algorithms	BPF	
	W-BPF	BPF with Weighted likelihood
	T-BPF	BPF with modified coordinated Turn model
	WVT-BPF	BPF with Weighted likelihood, limited Velocity and modified coordinated Turn model
Ranging Models	ML	Maximum Likelihood Trilateration
	NLR	Non-Linear Regression model
	V-BPF	BPF with limited Velocity
	EKF	Extended Kalman Filter
	WC-CWLS	Trilateration with Weighted Centroid and Constrained Weighted Least Square
	LLS	Linear Least Square Trilateration
	LDPL	Log-Distance Path Loss model

Table 2: Parameters for the NLR Model

	AN1	AN2	AN3	AN4	AN5
α	7.448	10.326	5.514	5.878	4.466
β	-0.03088	-0.0507	-0.04365	-0.05519	-0.05269

7 Performance Evaluation

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

7.1 Measurement Setup

The passive WiFi target tracking system has been deployed on the third floor of the INF building at the University of Bern. Figure 6(a) indicates one of the rooms in our challenging test environment with desktops, servers and iron cabinets. Five USRP receivers have been deployed in our working area as ANs to monitor the packets from a laptop as shown in Figure 6. A central server equipped with a 4-core i5 CPU (3.3GHz) is adopted to collect data from the five ANs and offline runs positioning algorithms for accuracy evaluation. In our measurements, the positioning target is a Thinkpad T430 laptop with an Intel N6300AGN wireless card. To evaluate our proposed tracking algorithms, the laptop is configured to continuously refresh a website to generate enough data traffic and the tracking accuracy is tested with legacy ACKs in IEEE 802.11n.

First, several initial measurements are conducted as shown in Figure 6(b). 11 training positions that spread over the whole area of interest are selected to acquire (α, β) in the NLR model. Based on these training positions, the (α, β) pairs for different ANs are calculated as in Table 2.

Second, tracking experiments along four different moving paths have been conducted to analyze the performance of the system for a mobile target, in which the laptop is held by a person and moves as indicated by the traces in Figures 6(c), 6(d), 6(e) and 6(f). The movement speed is around $0.88m/s$. Along the moving traces, positioning algorithms run every second to estimate the position of the moving target. The tracking accuracy is finally evaluated at 132 points along the four moving paths (blue circle points in Figures 6(c), 6(d), 6(e) and 6(f)).

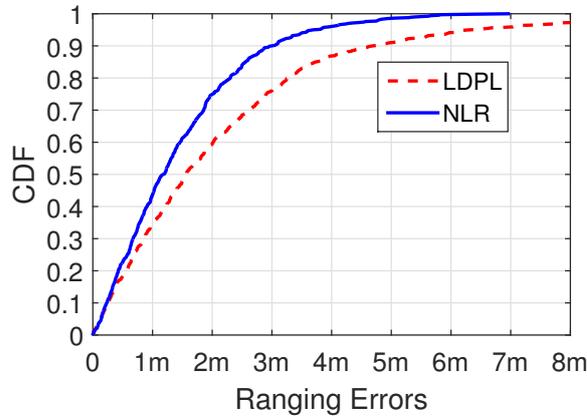


Figure 7: Ranging Errors with Different Ranging Models

7.2 Ranging Errors

Accurate ranging is a prerequisite for accurate range-based positioning. We calculate the ranging errors to each AN for the 132 test positions along 4 moving paths based on the NLR and LDPL models. Figure 7 indicates the Cumulative Distributed Functions (CDFs) of the ranging errors for both models. The NLR model achieves a median ranging error of $1.2m$ that is $0.4m$ smaller than the LDPL model. 90% of ranging errors with NLR are smaller than $3m$, which gets improved by 40% compared to LDPL. Therefore, we can conclude that with small training effort (only 11 training positions) the NLR model achieves high ranging accuracy, which is a prerequisite for accurate positioning, and significantly outperforms the LDPL model for the ranging step. Additionally, compared to fingerprinting methods, the training effort (11 training positions) is much lower.

7.3 Positioning Accuracy with Different Particle Numbers

The number of particles is a critical influencing factor on the performance of particle filters. Theoretically, more particles will improve the tracking accuracy but increase the computation effort. Therefore, we should choose a limited number of particles, which can still guarantee good performance. To investigate the performance of our proposed WVT-BPF with different numbers of particles, we adapt the numbers of particles from 100 to 1500 at steps of 100. For each number of particles, we run WVT-BPF on the four

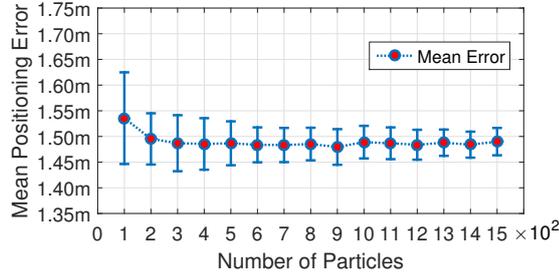


Figure 8: Positioning Errors with Different Numbers of Particles

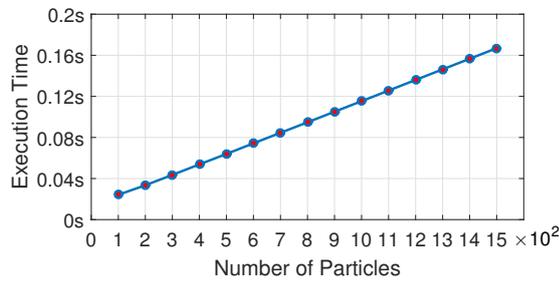


Figure 9: Execution Time with Different Numbers of Particles

paths 100 times and at each time we calculate the mean value of the positioning errors over the 132 positions (along four paths). Figure 8 indicates the mean values and standard deviations of positioning errors for each number of particles. In general, the mean and standard deviation of errors with WVT-BPF get smaller with larger numbers of particles. However, the improvement gets very marginal when the particle numbers are larger than 1000. Figure 9 indicates the execution time of the particle filter in the central server. The execution time linearly increases with larger numbers of particles. In our work, in order to achieve high tracking accuracy and limit the computation effort, we set the particle number to 1000.

7.4 Positioning Accuracy with the NLS Model

According to our measurements, ranging accuracy gets impressively improved under the NLS model. Therefore, in this subsection, we analyze the performance of our proposed enhanced particle filter with the NLS model. Since our proposed enhanced particle filter comprises three main improvements on the likelihood and moving models, we investigate the performance of each individual improvement, i.e., different versions of BPF

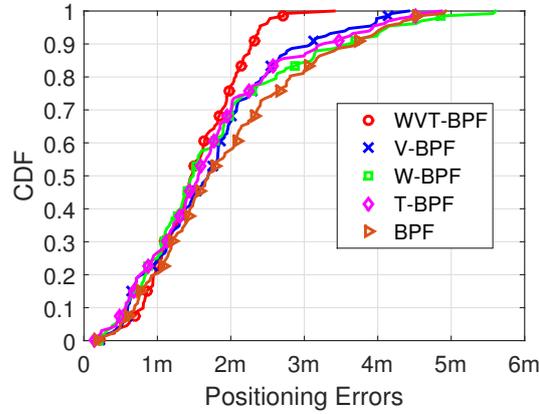
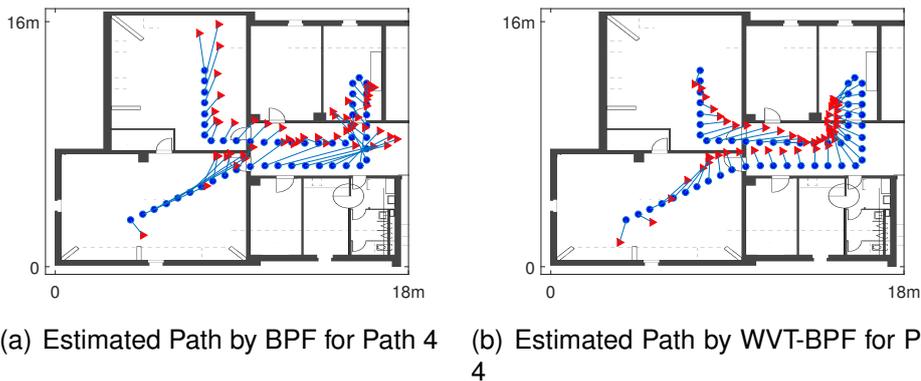


Figure 10: CDF of Positioning Errors for Different BPFs



(a) Estimated Path by BPF for Path 4 (b) Estimated Path by WVT-BPF for Path 4

Figure 11: Estimated Moving Path (Path 4) by BPF and WVT-BPF

as in Table 1. In addition, we compare the algorithm to other commonly used positioning algorithms, i.e., BPF, EKF, Triangulation algorithms with ML, LLS and WC-CWLS (Table 1).

Figure 10 indicates CDF of positioning errors for different versions of BPFs under the NLS model. First, after introducing the exponential weights to different individual likelihoods, W-BPF can mitigate the influence of ranging errors and correspondingly improve the positioning accuracy compared to the traditional BPF. Second, by filtering out the unreasonable particles with very large moving velocity in V-BPF, the estimated moving traces are smoothed and the positioning accuracy gets improved compared to BPF. Third, by considering the angle variation of the moving direction in the state vector, our proposed modified coordinated turn model further smooths the estimated moving path in T-BPF and this smoothness introduces an-

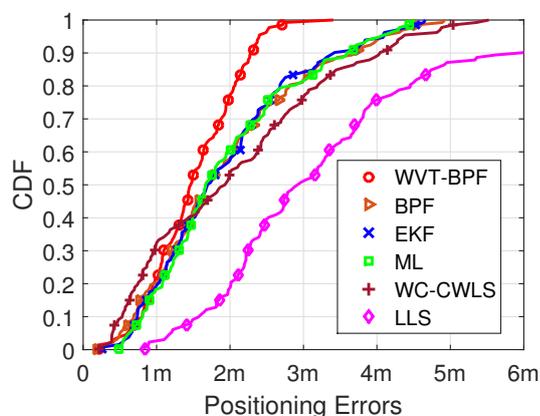


Figure 12: CDF of Positioning Errors under the NLS Model

other improvement to the positioning accuracy. Finally, by combining these three enhanced mechanisms, the median positioning error of our proposed WVT-BPF achieves around $1.5m$ and 90% of errors are smaller than $2.3m$, which significantly outperforms the traditional BPF. For example, 90% of tracking accuracy with WVT-BPF is better than $2.3m$, which is 38% more accurate than a traditional BPF ($3.7m$). Figure 11 shows an example of the estimated paths respectively by a traditional BPF and WVT-BPF for the fourth moving path. It is obvious that our proposed WVT-BPF can track the moving target with a much higher accuracy and the estimated moving path is more smooth.

Figure 12 shows CDF of positioning errors for different positioning algorithms with the NLS model. Our proposed WVT-BPF significantly outperforms the other positioning algorithms, i.e., BPF, EKF and trilateration algorithms. BPF, EKF and ML-based trilateration achieve very similar performance, which are slightly better than WC-CWLS. The performance of LLS is the worst. The median error of LLS is around $2.9m$, which is $1.4m$ worse than WVT-BPF and the 90% accuracy is around $6m$, which is $3.7m$ worse than WVT-BPF.

7.5 Positioning Accuracy under the LDPL Model

We further check the performance of our proposed enhanced particle filter under large ranging errors (with the LDPL model) and compare it to the other algorithms. Figure 13 shows CDFs of positioning errors for dif-

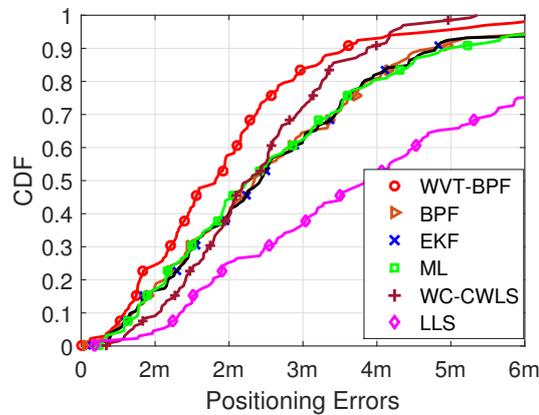


Figure 13: CDF of Positioning Errors with the LDPL Model

ferent positioning algorithms with the LDPL model. In the case of larger ranging errors by using the LDPL model, the performance of WVT-BPF deteriorates by 61% for the 90% positioning accuracy (from $2.3m$ to $3.7m$) compared to the NLR model. However, WVT-BPF still significantly outperforms the other positioning algorithms. Their performance deteriorates because of lower ranging accuracy. Similar to the results of our previous work [1], WC-CWLS, whose performance does not get significantly worse than with NLS model, is robust to ranging errors and outperforms EKF, BPF and ML-based trilateration. However, our proposed WVT-BPF still outperforms WC-CWLS. For example, the median error of our proposed WVT-BPF achieves $1.9m$, which is $0.2m$ better than WC-CWLS and the 90% positioning accuracy is $3.7m$, which is $0.3m$ better than WC-CWLS. In addition, by introducing the enhanced mechanisms in the particle filter, our proposed WVT-BPF is impressively better than BPF in the case of large ranging errors. For example, the median error of our proposed WVT-BPF is around $0.2m$ better than BPF ($2.1m$) and the 90% positioning accuracy is around $1.1m$ better than BPF ($4.8m$). With the LDPL model, LLS is significantly worse than the other positioning algorithms because it is very sensitive to ranging errors.

8 Conclusions

In this paper, we adopt software defined radio techniques to design a passive tracking system for mobile WiFi users. In this system, some enhanced ranging methods including channel information and nonlinear regression for ranging model are utilized to achieve highly accurate ranging and an enhanced particle filter (WVT-BPF) exclusively relying on power-based ranging with low calibration effort is further proposed to achieve high tracking accuracy. Our proposed WVT-BPF integrates three main novel improvements including weighted likelihood, velocity limitation on likelihood and a modified coordinated turn model. Each of the individual improvement can improve the tracking accuracy compared to the traditional BPF. By integrating all these improvements, our proposed WVT-BPF outperforms the traditional BPF, EKF, and trilateration algorithms. By combining WVT-BPF with the enhanced ranging methods, our system can passively track the WiFi target with an accuracy of $1.5m$ for 50% and $2.3m$ for 90%.

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