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Super Resolution WiFi Indoor Localization and Tracking

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***Abstract*—In this paper, we present a complete framework for accurate indoor positioning and tracking using the 802.11a Wi-Fi network. Channel frequency response is first estimated via the least squares (LS) method using an orthogonal frequency division multiplexing (OFDM) pilot symbol. For accurate time of arrival (ToA) distance estimates in multipath environments, super resolution technique i.e. MUltiple SIgnal Classification (MUSIC) is used which capitalizes on the autocorrelation matrix of the estimated channel frequency response. The estimated distances from the base stations (BSs) are then used in the observation model for particle filter (PF) tracking for which a constant velocity motion model is used, depicting indoor mobile movement. The tracking performance of the combined MUSIC-PF is compared with PF performance when a conventional cross correlator (CC) is used for delay estimates. It is shown via simulation that the PF-MUSIC performance is superior to the PF-CC performance.**

***Index Terms*—Localization, tracking, WiFi networks.**

I. Introduction

INDOOR localization has been of great interest to researchers in the last decade [1]. Location information of objects (or humans) will be an integral part of the Internet of things (IoT) paradigm. Indeed, new technologies such as the impulse based ultra wide band (UWB) technology, courtesy to its large bandwidth, offers exceedingly high timing and hence distance estimate accuracy [2]. However, it will require the installation of new indoor wireless infrastructures. Thus the aim now is to use existing indoor wireless technologies i.e. the IEEE 802.11a WiFi for cost effective indoor localization and tracking. The first step in most localization systems is the accurate distance estimates between the mobile device (MD) and fixed base stations (BSs) or anchors. Although coarse distance estimates can be obtained using the attenuation of the signal, the time of arrival (ToA) has been a very successful strategy for accurate distance estimates [3]. However, its accuracy is limited to the bandwidth of the underlying physical layer signal. In case of the 802.11a standard, a bandwidth of 20 MHz is allowed [4], which translates into a sample rate of 50 ns. Thus when a conventional cross correlator (CC) is used for delay estimation, in the worst case, a delay that is midway between two samples will have an error of 7.5 m associated with it. This clearly is unacceptable especially in indoor scenarios. Although, sub sample interpolation based techniques have been proposed to improve the delay estimate accuracy [5], frequency domain techniques such as the preeminent MUltiple SIgnal Classification (MUSIC) and its derivatives have proved to provide superior performance [6]. The MUSIC algorithm, originally developed for bearing estimation, has recently been adopted for multipath delay estimation [7]. MUSIC operates on the autocorrelation of the estimated channel frequency response. Thus the first step is the estimation of the multipath channel frequency response, which in this paper is achieved by the least squares (LS) technique using the *block* type orthogonal frequency division multiplexing (OFDM) pilot symbol [8]. Distance estimates are readily available once the first arriving multipath or direct line of sight (LoS) is obtained from all BSs via MUSIC algorithm.

The distance estimates from a minimum of three BSs are used in the observation model for tracking purposes. However these distance estimates are highly non-linear in terms of the location coordinates of the MD. Traditional tracking algorithms such as Kalman filter (KF) [9] are optimal in linear observations and Gaussian noise. For nonlinear observations, techniques such as the extended Kalman filter (EKF) [10], [11] can be adopted in which the non-linear distance estimates are first linearized via first order Taylor series. Other approaches may include the unscented Kalman filter (UKF) [12] which is deemed more accurate than the EKF.

To overcome the limitations of the KF and its variants, in recent years the focus of research has shifted to Monte Carlo based methods, such as particle filters (PFs) [13]. PF numerically approximates the nonlinear filtering problem by first generating a set number of random samples (particles), then *predicting* and *updating* them via the prior and likelihood probability density functions (pdfs) respectively. In this paper, we present the combined MUSIC-PF algorithm which utilizes the super resolution delay estimation of MUSIC and also demonstrates the superior tracking performance of the PF.

The rest of the paper is organized as follows. Section II describes the signal model of the 802.11a WiFi systems, it also presents the LS estimation of the channel frequency response and the MUSIC algorithm. Section III deals with the localization and tracking of the MD. In section IV, we present the simulation results which are followed by the conclusions.

II. Signal Model

For future use, the following notations are defined. $\mathscr{R}^n$ is the set of n dimensional real numbers. $(.)^T$ and $(.)^H$ represent the transpose and Hermitian transpose operation. $E(.)$ refers to the expectation operation. $\mathbf{I}$ represents the identity matrix. $\mathcal{N}(\mu, \sigma^2)$ denotes the normal distribution with mean μ and variance σ^2. $\otimes$ represents the circular convolution.

The discrete time OFDM signal is represented by

$$x[n] = \sum_{k=0}^{N-1} X(k) \exp\left(\frac{j2\pi kn}{N}\right) \qquad \text{for } n = 0, 1, ..., N-1, \tag{1}$$

where $X(k)$ is data symbol and N is the number of sub-carriers.

The cyclic prefix (CP) is inserted as the guard interval to avoid inter symbol interference (ISI).

$$\bar{x}[n] = \begin{cases} x[N+n] & \text{for } n = -N_{CP}, -N_{CP}+1, ..., -1 \\ x[n] & \text{for } n = 0, 1, ..., N-1 \end{cases} \tag{2}$$

where N_{CP} is the number of CP symbols.

The received discrete time signal can now be given as

$$\bar{y}[n] = \bar{x}[n] \otimes h[n] + w[n], \tag{3}$$

where $w[n]$ is the additive white Gaussian noise (AWGN) and $h[n]$ is the discrete time channel impulse response i.e.

$$h[n] = \sum_{l=0}^{L-1} a_l \delta(nT_s - \tau_l), \tag{4}$$

T_s being the sampling rate. L is the number of multipaths and $\delta(.)$is the Dirac delta function. a_l and τ_l is the complex attenuation and delay of the l^{th} path.

The CP is removed at the receiver and the received symbols are obtained after the fast Fourier transform (FFT) operation

$$Y(k) = \frac{1}{N} \sum_{n=0}^{N-1} y(n) \exp\left(-\frac{j2\pi kn}{N}\right). \tag{5}$$

If there is no ISI, due to large enough CP then the received OFDM signal $Y(k)$ can be represented by

$$Y(k) = X(k) H(k) + W(k), \tag{6}$$

where $W(k)$ is the Fourier transform of $w(n)$ and $H(k)$ is the channel transfer function which can be represented by

$$H(k) = \sum_{l=0}^{L-1} a_l \exp\left(-\frac{j2\pi k\tau_l}{T_s}\right) \tag{7}$$

or

$$H(f_k) = \sum_{l=0}^{L-1} a_l \exp(-j2\pi f_k \tau_l) \tag{8}$$

for $f_k = \frac{k}{T_s}$ and $k = 0, 1, ..., N-1$.

When the block type pilot symbol $\mathbf{X}_p$ is used, the LS channel frequency response can be estimated as

$$\hat{\mathbf{H}} = \mathbf{X}_p^{-1} \mathbf{Y}, \tag{9}$$

where $\mathbf{X}_p = \text{diag}[X_p(1), \cdots, X_p(N-1)]$ and $\mathbf{Y} = [Y(1), \cdots, Y(N-1)]^T$.

The estimated channel transfer function can then be modeled as

$$\hat{\mathbf{H}} = \mathbf{H} + \mathbf{w} = \mathbf{V}\mathbf{a} + \mathbf{w} \tag{10}$$

where

$$\hat{\mathbf{H}} = \begin{bmatrix} \hat{H}(f_0) & \hat{H}(f_1) & \cdots & \hat{H}(f_{N-1}) \end{bmatrix}^T$$

$$\mathbf{H} = \begin{bmatrix} H(f_0) & H(f_1) & \cdots & H(f_{N-1}) \end{bmatrix}^T$$

$$\mathbf{w} = \begin{bmatrix} w(0) & w(1) & \cdots & w(N-1) \end{bmatrix}^T$$

$$\mathbf{V} = \begin{bmatrix} \mathbf{v}(\tau_0) & \mathbf{v}(\tau_1) & \cdots & \mathbf{v}(\tau_{L-1}) \end{bmatrix}^T$$

$$\mathbf{v}(\tau_l) = \begin{bmatrix} 1 & \exp(-j2\pi f_1 \tau_l) & \cdots & \exp(-j2\pi f_{N-1} \tau_l) \end{bmatrix}^T$$

$$\mathbf{a} = \begin{bmatrix} a_0 & a_1 & \cdots & a_{L-1} \end{bmatrix}^T.$$

The autocorrelation matrix of the estimated channel transfer function is then given by

$$\mathbf{R}_{\hat{H}\hat{H}} = E\left[\hat{\mathbf{H}}\hat{\mathbf{H}}^H\right] = \mathbf{V}E\left\{\mathbf{a}\mathbf{a}^H\right\}\mathbf{V}^H + \sigma_w^2 \mathbf{I}. \tag{11}$$

With the assumption that $E\left\{\mathbf{a}\mathbf{a}^H\right\}$ is non-singular and $\mathbf{V}$ is full rank due to all values of τ_l being different. If $\lambda_0 \geq \lambda_1 \geq, \ldots, \geq \lambda_{N-1}$ represent the eigen values of the the autocorrelation matrix $\mathbf{R}_{\hat{H}\hat{H}}$. Then it follows that the corresponding eigen vectors $\mathbf{e}_i$ spaning the space of dimension N can be split into two orthogonal sub-spaces $\mathbf{E}_s$ and $\mathbf{E}_n$. Where $\mathbf{E}_s = [\mathbf{e}_0, \mathbf{e}_1, \ldots, \mathbf{e}_{L-1}]$ corresponding to eigen values $\lambda_i > \sigma_w^2$, lie in the signal subspace while eigen vectors $\mathbf{E}_n = [\mathbf{e}_L, \mathbf{e}_{L+1}, \ldots, \mathbf{e}_{N-1}]$ corresponding to $\lambda_i < \sigma_w^2$, lie in the noise subspace. The noise projection matrix $\mathbf{P}_w$ can now be formulated as

$$\mathbf{P}_w = \mathbf{E}_n \mathbf{E}_n^H. \tag{12}$$

Since the vector $\mathbf{v}(\tau_l)$ lie in the signal subspace, it is orthogonal to the the projection matrix $\mathbf{P}_w$. The MUSIC algorithm finds the delay $\mathbf{v}(\tau_l)$ for which

$$\mathbf{P}_w \mathbf{v}(\tau_l) = 0 \tag{13}$$

or alternatively those τ_l which maximize the pseudo spectrum

$$\mathcal{S}_{MUSIC} = \frac{1}{\|\mathbf{P}_w \mathbf{v}(\tau_l)\|^2}. \tag{14}$$

Thus in multipath environments, $L-1$ peaks are obtained using the MUSIC algorithm from the pseudo spectrum. For ToA and hence distance estimation, the first peak on the delay axis is selected. The first detected peak could correspond to a LoS delay or a multipath with the smallest positive bias. Once the distance estimates are obtained from at least 3 BSs, localization and tracking techniques can be applied as discussed in the next section.

III. Localization and Tracking of Mobile Device

We consider a two dimensional network with one MD which has unknown coordinates $\boldsymbol{\theta} = [x, y]^T \left(\boldsymbol{\theta} \in \mathscr{R}^2\right)$ at any given time that are to be estimated referenced to M BSs with known locations $\boldsymbol{\theta}_i = [x_i, y_i]^T \left(\boldsymbol{\theta}_i \in \mathscr{R}^2\right)$ $i = 1, ..., M$. The MD is assumed to have on board sensors that measure velocity, orientation etc.

A. Motion model

Numerous motion models have been suggested in literature such as random walk, Singer type model [14]. For indoor localization, in this paper, we assume a basic constant velocity model. The state space vector is given by $\boldsymbol{x} = [x, y, v_x, v_y]^T$, where v_x and v_y represent the velocity in the x and y direction. The constant velocity model is then given by

$$\boldsymbol{x}_t = \mathbf{F}\boldsymbol{x}_{t-1} + \boldsymbol{n}_t, \tag{15}$$

where $\mathbf{F}$ is the transition matrix and is given by

$$\mathbf{F} = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

T is the discretization period and $\boldsymbol{n}_t$ is the Gaussian process noise at the t^{th} step. Its covariance is given by $\mathbf{C} = \sigma_n^2\mathbf{I}$.

B. Observation model

The estimated delay $\hat{\tau}_i$ from the i^{th} BS based on the first peak of the pseudo spectrum can be used to estimate the distance $\hat{d}_i$, i.e. $\hat{d}_i = c\hat{\tau}_i \ \left(c \approx 3 \times 10^8\right)$, where it can be modeled as

$$\hat{d}_i = d_i + m_i, \tag{16}$$

where d_i is the actual distance given by

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{17}$$

and m_i is the associated Gaussian noise. The measurement equation can thus be written as

$$\boldsymbol{z}_t = \boldsymbol{h}(\boldsymbol{x}_t) + \boldsymbol{m}_t, \tag{18}$$

where $\boldsymbol{h}(\boldsymbol{x}_t) = \left[\hat{d}_1, \ldots, \hat{d}_M\right]^T$, the noise vector $\boldsymbol{m}_t$ has a covariance matrix $\mathbf{R} = \text{diag}\left[\hat{\sigma}_1^2, \ldots, \hat{\sigma}_M^2\right]$, where $\hat{\sigma}_i^2$ is the noise variance associated with the distance estimate from the i^{th} BS. Since the eigen values $\lambda_L, \ldots, \lambda_{N-1}$ correspond to noise eigen vectors, and is an indication of the noise variance, the variance in delay and hence distance estimate from the i^{th} BS can be estimated by taking the average of all noise eigen values for the i^{th} BS i.e.

$$\hat{\sigma}_i^2 \approx \sum_{j=L}^{N-1} \lambda_j^i. \tag{19}$$

C. Particle filter

This subsection highlights the operation of the PF for indoor MD tracking. PF [13] is an implementation of the Monte Carlo methods for sequential Bayesian filtering. Bayesian filters aims to operate on the posterior pdf of the state vector. As new information is made available the recursive Bayesian filter updates the posterior pdf of the state vector. If the observation model is linear and the all the noise components can be assumed Gaussian then the recursive Bayesian filter reduces to the KF.

PFs, on the other hand, approximate the posterior pdf numerically with random samples (particles). The approximation accuracy depends on the number of particles. The particles once generated randomly are propagated and updated based on the motion and observation model respectively. PFs do not require the observation model to be linear or the noise to be Gaussian.

The recursive Bayesian formula to obtain the posterior $p(\boldsymbol{x}_{1:t}|\boldsymbol{z}_{1:t})$ from $p(\boldsymbol{x}_{1:t-1}|\boldsymbol{z}_{1:t-1})$ is given by

$$p(\boldsymbol{x}_{1:t}|\boldsymbol{z}_{1:t}) = \frac{p(\boldsymbol{z}_t|\boldsymbol{x}_t)\, p(\boldsymbol{x}_t|\boldsymbol{x}_{t-1})}{p(\boldsymbol{z}_t|\boldsymbol{z}_{1:t-1})} p(\boldsymbol{x}_{1:t-1}|\boldsymbol{z}_{1:t-1}), \tag{20}$$

where $\boldsymbol{z}_{1:t}$ is the set of all observation up to time step t.

The posterior pdf can be approximated by a set of N_s particles $\boldsymbol{x}_{1:t}^i$ with associated weights w_t^i, i.e.

$$p(\boldsymbol{x}_{1:t}|\boldsymbol{z}_{1:t}) = \sum_{i=1}^{N_s} w_t^i \delta\left(\boldsymbol{x}_{1:t} - \boldsymbol{x}_{1:t}^i\right). \tag{21}$$

Here the particles are generated from a proposed *importance function* or *proposal density* $q(\boldsymbol{x}_{1:t}|\boldsymbol{z}_{1:t})$ and the weights w_t^i are given by

$$w_t^i = \frac{p\left(\boldsymbol{x}_{1:t}^i|\boldsymbol{z}_{1:t}\right)}{q\left(\boldsymbol{x}_{1:t}^i|\boldsymbol{z}_{1:t}\right)}. \tag{22}$$

Now if the proposal density is chosen such that

$$q(\boldsymbol{x}_{1:t}|\boldsymbol{z}_{1:t}) = q(\boldsymbol{x}_t|\boldsymbol{x}_{t-1}, \boldsymbol{z}_t)\, q(\boldsymbol{x}_{1:t-1}|\boldsymbol{z}_{1:t-1}). \tag{23}$$

Then from (20), (22) and (23), the weights are given by

$$w_t^i \propto \frac{p\left(\boldsymbol{z}_t|\boldsymbol{x}_t^i\right) p\left(\boldsymbol{x}_t^i|\boldsymbol{x}_{t-1}^i\right)}{q\left(\boldsymbol{x}_t^i|\boldsymbol{x}_{t-1}^i, \boldsymbol{z}_t\right)} w_{t-1}^i. \tag{24}$$

A straightforward approach is to select the prior $p(\boldsymbol{x}_t|\boldsymbol{x}_{t-1})$ as the proposal density i.e. $q\left(\boldsymbol{x}_t^i|\boldsymbol{x}_{t-1}^i, \boldsymbol{z}_t\right) = p\left(\boldsymbol{x}_t^i|\boldsymbol{x}_{t-1}^i\right)$, which reduces (24) to

$$w_t^i \propto p\left(\boldsymbol{z}_t|\boldsymbol{x}_t^i\right) w_{t-1}^i. \tag{25}$$

Finally, since we are only interested in the state vector at the current time step t, the marginalized density $p(\boldsymbol{x}_t|\boldsymbol{z}_{1:t})$ is given by

$$p(\boldsymbol{x}_t|\boldsymbol{z}_{1:t}) = \sum_{i=1}^{N_s} w_t^i \delta\left(\boldsymbol{x}_t - \boldsymbol{x}_t^i\right). \tag{26}$$

A *resampling* procedure follows to reduce the degeneracy problem. Degeneracy occurs when all particles except a few are given negligible weights which impairs the performance of the particle filter.

To explain (20)-(26) in words, basically two steps; *prediction* and *update* are involved. During the prediction stage a set of particles with corresponding weights are passed through the motion model where random noise is also added to simulate the effects of state noise. These particles are then reweighed on the basis of newly available observation data, thus the approximation of the posterior density at the current time step is completed. The state vector can then be estimated by taking the mean of the posterior density. Finally resampling is performed. The combined MUSIC-PF steps are described in Algorithm 1.

Algorithm 1 MUSIC-PF Algorithm

Initialization

I. MUSIC

For $t = 1, ...,$

1) For $j = 1, ..., M$

-Perform LS channel estimation to estimate $\hat{\mathbf{H}}$ for each BS.

-Generate autocorrelation matrix $\mathbf{R}_{\hat{H}\hat{H}}$ and apply MUSIC algorithm for each BS.

-Estimate distance from the first delay estimate and set $\mathbf{R} = \mathrm{diag}\left[\hat{\sigma}_1^2, \cdots, \hat{\sigma}_M^2\right]$.

II. PF

2) Generate samples $\left\{\boldsymbol{x}_0^{i*} \sim \mathcal{N}\left(\mu_0, \sigma_0^2\right)\right\}$, $i = 1, ..., N_s$. Set $t = 1$ and $w_0^{i*} = \frac{1}{N_s}$.

(3) ***prediction step***

For $i = 1, ..., N_s$ predict according to

$$\boldsymbol{x}_t^i = p\left(\boldsymbol{x}_t | \boldsymbol{x}_{t-1}^{i*}\right),$$

which is simply done by passing the generated samples through the state equation

$$\boldsymbol{x}_t^i = \mathbf{F}\boldsymbol{x}_{t-1}^{i*} + \boldsymbol{n}_t^i$$

(3) ***update step***

update weights according to

$$w_t^i = p\left(\boldsymbol{z}_t | \boldsymbol{x}_t^i\right) w_{t-1}^i$$

Normalize weights $\widetilde{w}_t^i = \frac{w_t^i}{\sum_{i=1}^{N_s} w_t^i}$.

(3) ***estimate output***

The state is estimated by the mean of the posterior i.e.

$$\hat{\boldsymbol{x}}_t = E\left\{p\left(\boldsymbol{x}_t | \boldsymbol{z}_t\right)\right\}$$

or

$$\hat{\boldsymbol{x}}_t = \frac{1}{N_s}\sum_{i=1}^{N_s} \widetilde{w}_t^i \boldsymbol{x}_t^i$$

resample if required. Set $t = t + 1$ and $w_t^i = \frac{1}{N_s}$.

IV. Performance Evaluation

PF tracking using OFDM signals based on the IEEE 802.11a standard are used for the simulation purposes. The IEEE 802.11a employs a 64 sub-carrier symbol, in which 53 sub carriers are for useful data. Channel estimation can be performed either using a comb type pilot or a block type. In comb type arrangement the pilots are uniformly distributed within each OFDM symbol, however we have chosen the block type pilot arrangement for channel estimation in this paper, in this type, the pilot signals form one complete OFDM symbol which spreads across all sub-carriers. A CP size of 10 is used to avoid ISI. Simulation parameters are given in table I.

Five BSs are positioned at $[(0,0), (50,0), (50,100), (50,50), (0,100)]$, to locate and track the MD which moves at a constant velocity of 1m/s, while the MD is allowed abrupt changes in its direction. The time step T for each observation is considered 1s and the motion model noise variance $\sigma_n^2 = 1$. For all BSs, three multipaths are considered i.e. $L = 2$, with random delay between 1-10 ns.

Parameter	Value
BW	20 MHz
Symbol duration	3.2 μs
No. of sub-carriers	64
No. of used subcarriers	52
CP	10
Pilot type	Block

Table I
SIMULATION PARAMETERS BASED ON THE IEEE 802.11A STANDARD

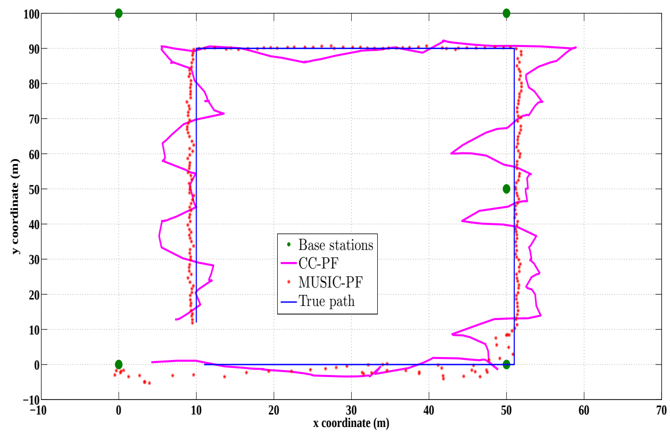

Figure 1. Comparison between MUSIC-PF and CC-PF techniques.

Fig. 1 shows the performance comparison between the CC-PF and MUSIC-PF algorithms, the true trajectory of the MD is also shown. It is evident that the MUSIC algorithm along with PF outperforms the CC-PF. After the initial transient stage, the MUSIC-PF converges and follows the true path of the MD closely. On the other hand, the CC-PF, due to coarse range estimates of the CC in multipath scenarios performs poorly and shows unacceptable variation around the true path.

Fig. 2, compares the root mean square error (RMSE) at each time step between CC-PF and MUSIC-PF. The RMSE value

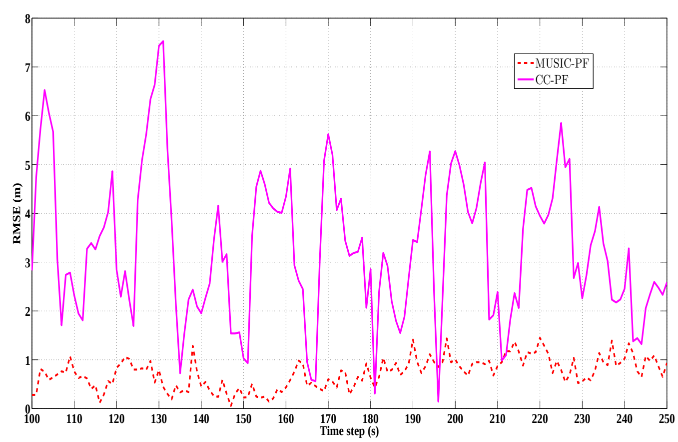

Figure 2. RMSE comparison between MUSIC-PF and CC-PF algorithm.

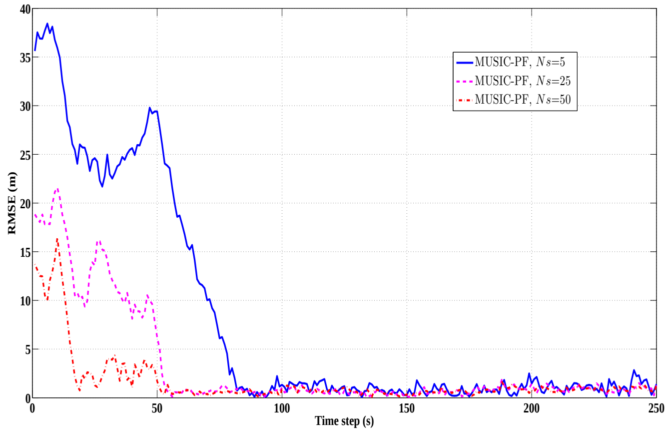

Figure 3. RMSE comparison of MUSIC-PF for different number samples.

at the t^{th} time step is obtained as

$$RMSE_t = \sqrt{(\hat{x}_t - x_t)^2 + (\hat{y}_t - y_t)^2},$$

where $(\hat{x}_t, \hat{y}_t)$ and (x_t, y_t) represent the estimated and true coordinates at the t^{th} time step. It is again evident from Fig. 2 that the MUSIC-PF outperforms CC-PF by a considerable margin.

Fig. 3, compares the performance of the MUSIC-PF algorithm with different number of particles. It is seen that a good transient performance is shown with a large number of particles. However the performance of the PF is unaltered after convergence even with a small number of particles.

V. Conclusions

In this paper, we presented a framework for accurate multipath indoor localization and tracking of mobile nodes. Accurate delay estimation of OFDM signals based on the IEEE 802.11a standard is performed via the super resolution MUSIC technique and tracking is done via PF. The combined MUSIC-PF algorithm begins with the estimation of the channel transfer function, which is then used to generate autocorrelation matrix, on which the MUSIC algorithm operates for delay estimation. Once the delay (and hence the distance) information from all BSs is made available, it is used in the observation model for PF tracking. A simplistic constant velocity motion model is considered for indoor MD movement. It is shown via simulation result that the performance of the MUSIC-PF algorithm supersedes that of CC-PF in which the multipath delay estimation is done via a conventional CC.

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