Localization of Mobile Nodes in Wireless Networks with Correlated in Time Measurement Noise

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Abstract-
Wireless Sensor Networks (WSNs) are widely used in applications like location monitoring, object tracking and decision making systems. Movement patterns of mobile sensor nodes play an important role in such systems. This paper is aimed at simultaneous localization of mobile nodes. This is done based on RSSIs (Received Signal Strength Indicators) with correlated in time measurement noises. We proposed a framework with two multi model auxiliary particle filters. The first one is with a noise augmented state vector while the second one is to implement noise decorrelation. The performance of the proposed framework is validated using a simulator and the empirical results revealed that our framework provides high localization accuracy.

Keywords—localization, WSN, correlated measurement noise, auxiliary particle filtering.

I. INTRODUCTION

In wireless networks mobile users move freely in given area. Finding their patterns is an important task. It does mean that localization of mobile nodes has important applications in wireless networks. Using this object tracking, sensor data fusion, and decision making [17], [22] kind of tasks can be done easily and for this localization of the positions of nodes and their movement [21], [23] is essential. Other motivating examples of wireless networks are monitoring of warehouses, production processes. The nodes in wireless network have limitations in terms of energy and bandwidth. With this constraint, processing noisy data is a challenging job. To improve the possibilities in mobile networks, location methods are invented. However, the range based methods as discussed in [6], [18], and [12] are widely used. They are evaluated using RSS, angle of arrival or difference of arrivals, signal time of arrivals as they depend on distances between nodes. The techniques which are based on rage are further divided into acoustic ranging and radio frequency (RF). In case of RF, it is possible to find the distance between the transmitter and receiver based on the signal strength. Another approach is to find difference of arrival of ultrasonic and acoustic signals [18], [24]. Range based algorithms only need information like distance, angle and positioning of nodes while the range-free algorithms do not need such information. These are further sub divided into outdoor and indoor environments [7]. Many methods pertaining to localization depend on Carlo methods [15], [16], Kalman filters [14], [19] and also nonparametric belief propagation [8] and the connectivity know how among the nodes. Due to bandwidth and energy constraints, the communication between nodes while location is reduced to minimum. Multiple model particle filtering techniques were introduced in [25] and [11]. They are used for tracking mobility of users of mobile networks. The filtered used here are compared with Kalman filter with real and simulation data from base stations.

Multiple model particle filter is proposed in [20], [5] solving tracking problems. A different approach is used in [20] where multiple off springs are derived from a single particle. Each offspring represents a target maneuver and hence it is known as maneuvering target tracking.

In binary sensor networks PF is used in target tracking as described in [13]. Its drawbacks are overcome by a new approach proposed in [10]. Many of the approaches discussed so far are able to localize mobile devices. However, they are not considering correlated measurement noise. In [17] a common correlation model is used. Decreasing autocorrelation function is used in Gudmunsson. In [3], autoregressive correlation model is used along with another filter named Kalman filter. In [4] the study of shadow fading is done. In this paper we present a new solution to the self localization problem considering temporal correlation in the measurement noise. This paper has innovative aspects when compared with prior works. It makes use of multiple model auxiliary particle filters. The empirical results with simulations on real and synthetic data have been validated. Autoregressive model is used to model correlated noise as described in [1]. Two approaches have been used namely state vector and decorrelation with differenced measurement [2]. Two algorithms have been proposed in this paper in order to make experiments with and without considering correlated measurement noise. The mobility model is based on the discrete-time command Markov process (linear system) while the measurement models are nonlinear. As the mobile nodes control process is known, the node mobility is modeled with multiple acceleration modes.

II. MOTION MODEL FOR THE MOBILE NODES

A. Observation Model

RSSIs (Received Signal Strength Indicators) can be used to measure the distance between mobile node and other node who involve in communication. It does mean that distance between transmitter and receiver. The received RSSI (zlj, k) at mobile node Nl with coordinates (xl, k, yl, k) at time k, after it has been transmitted from node Nj with its coordinates (xj, k, yj, k), propagates [21], [1] as follows.

$z_{lj,k} = k_l - 10_\gamma \log_{10}(d_{lj,k}) + v_{lj,k,}$

B. Correlated In Time Measurement Noise

The shadowing component or autocorrelation function of the measurement noise (ulj, k) in urban and suburban environments is modeled as follows [1], [3].

$C_v(r) = \sigma_v^2 \exp\{-v|r|/D_c\},$

where τ is the time lag, σ_v is standard deviation, of the shadowing process, Dc denotes effective correlation distance. The Dc is very important in a wireless environment and v is the velocity of the mobile node.

III. A Multiple Model Auxiliary Particle Filtering for Localization

A. The Particle Filtering Framework

The localization of mobile nodes within the particle filtering can be reduced to approximation of PDF (Probability Density Function) based on the sequence of measurements. As per the Bayes' rule the filtering PDF $p(X_k|Z_{1:k})$ of the state vector

$X_k \varepsilon \mathbb{R}^{n^* n_x}$ based on a sequence of sensor measurements Z1:k up to time k. It can be written as follows.

$$p(X_k|Z_{1:k}) = \frac{p(Z_k|X_k)p(X_k|Z_{1:k-1})}{p(Z_k|Z_{1:k-1},)}$$

where $(Z_k |Z_{1:k-1})$ is he normalizing constant.

B. Auxiliary Multiple Model Particle Filtering for Localization

Pitt and Shephard [9] introduced the auxiliary SIR (Sampling Importance Resampling) PF. The PD draws particles from something which is close to possible optimal one. That something is known as importance function. Algorithm 2 presents the MM AUX-PF for mobile nodes localization. It takes speed constraints into account. The speed can't exceed Vmax. Only when efficient number of particles, Neff is smaller than given threshold Nthresh resampling is performed.

Algorithm: A multiple model auxiliary PF for mobile nodes localization

Initialization

I . K=0, for i=1, ……. $N_{(i)}$

Generate samples { $x_0^{(i)} \sim p(X_0)$, $M_0^{(i)} \sim Po(M)$ } ,

And set initial weights $w_o^{(i)} = 1/N$

II. Fork k= 1,2,……

(1) For i = 1 ………,N * r,

Calculate the conditional mean:

$\mu_k^{(i)} (M_K) = E (X_k \text{ I } X^{(i)}_{k-1} ,M_k)$ for every $M_k \varepsilon S$

(2) Generate $\{i^j, M_k^{(j)}\}$ j=1, ….., N

by sampling from $q(I,M_k|Z_{1:k})$,

where $q(i,M_k|Z_{1:k}) \alpha\, p(Z_k|\mu_k^{(i)} (M_k))p(M_k|M_{k-1}^{(i)})\, w^{(i)}_{k-1}$.

(3) Prediction Step

For j=1,…….,N, predict the particles according to

$X^{(j)}_k = f(X_{k-1}^{ij}, M^{(j)}_k, w^{(j)}_k)$

With noise realizations $w_k^{(j)} \sim N(0,Q)$.

Impose the speed constraints.

(4) Measurement update

For j=1,……,N compute the weights

$W_k^{(j)} = p(Z_k|X_k^{(j)})/p(Z_k|\mu_k^{(ij)} (M_k))$.

Normalise the weights: $w_k^{\sim(j)} = w_k^{(j)} / \sum^N_{j=1} w_k^{(j)}$

(5) Output estimate

The posterior mean $E[X_k|z_k]$

$\hat{x}_k = \sum^N_{j=1} w_k^{\sim(j)} x_k^{(j)}$.

(6) Resampling step:

Compute the effective sample size

$N_{eff} = 1/\sum^N_{j=1} (w_k^{\sim(j)})^2$,

Resample if $N_{eff} < N_{thresh}$

*For i=1,………,N, set $w_k^{(i)} = 1/N$.

Fig. 1: Algorithm for multiple model auxiliary PF for mobile nodes localization

IV. Implementation

In addition to sensor deployment architecture presented in [13] (as described in section 5.1), a custom simulator has been developed using C# programming language in order to demonstrate the concept of localization of mobile nodes in WSN. The implementation is done using Win Forms technology in C#. The GUI is as shown in fig. 2.

(a) (b)

Fig. 2: GUI of the application

As can be seen in fig.2 (a), a provision is given to specify number of nodes for simulation. On clicking Create button, the nodes are randomly created as shown in fig. 2 (b).

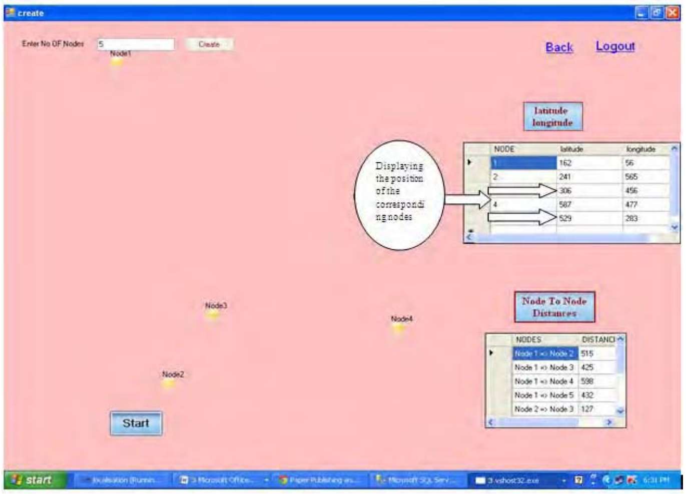

Fig. 3: Longitude and Node to Node distances

As can be seen in fig. 3, sensor nodes are randomly located on the field. In the above screen it shows 6 nodes randomly distributed. Nodes' longitude and latitude are also shown in grid view. The distance between mobile nodes is also shown in another grid view in fig. 3.

The application also has provision to have clusters and nodes can be associated with clusters. Node to cluster distances and node regions are presented in fig. 4.

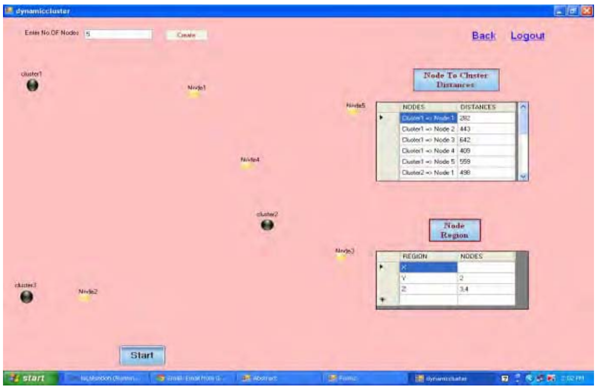

Fig. 4: Nodes and Clusters

As can be seen in fig. 4, there are three clusters formed and nodes are associated with the clusters. On clicking the Node to Cluster Distances button a grid view is shown and it contains cluster to node distances. Nodes belong to certain regions. On clicking, Node Region button the region and the nodes belong to the regions is shown in another grid view.

V. PERFORMANCE EVALUATION

A. Results with Simulated Data

Sensor deployment architecture presented in [13] is used for the experiments. In Urban area, three mobile sensors are moving within the Wireless Sensor Network. Each node can measure RSSI of other node based on the signal strength. However, only the RSSIs with highest strength are used for localization.

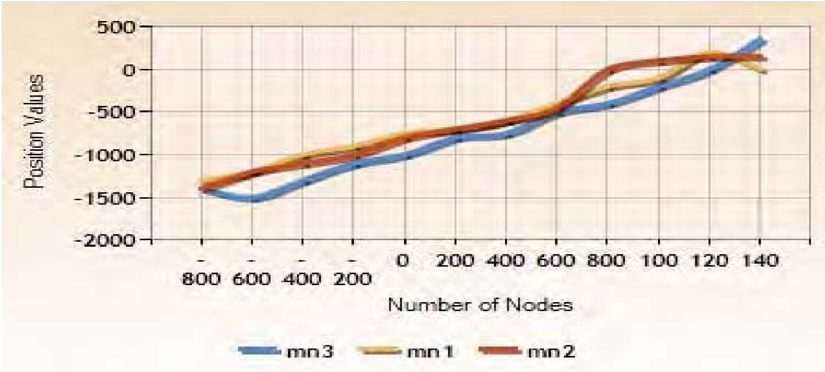

Fig. 5: Three mobile nodes in WSN

Table1: Representation for strength of mobile nodes

S.No	Nodes	Parameters
1	Mn1	-1400,-1500,-1300,-1100,-1000,-800,-750,-500,-400,-200,0,350
2	Mn2	-1300,-1200,-1000,-900,-750,-700,-600,-400,-200,-100,200,0
3	Mn3	-1400,-1200,-1100,-1000,-800,-700,-600,-450,0,100,150,150

As can be seen, the fig. 5 presents the estimated and actual trajectories of the three mobile nodes. The MM AUX-PF AS is executed for estimating the augmented state vector. This vector contains the mobile state vectors of three nodes. Actual speed of the mobile nodes is visualized in fig.6.

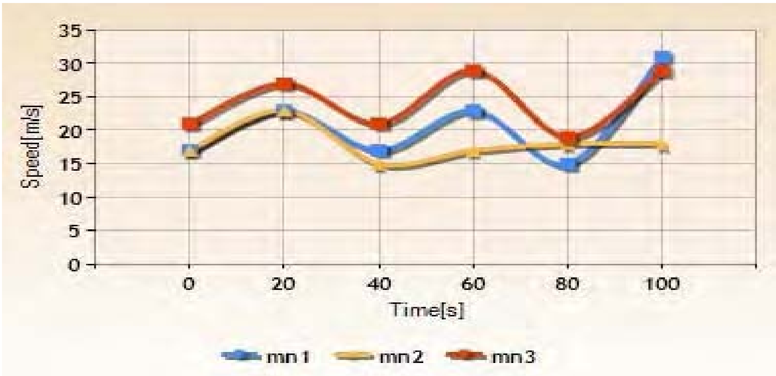

Fig. 6: Actual speed of three moving nodes

Table2: Representation for speed of moving nodes

S.No	Nodes	Parameters
1	Mn1	17,23,17,23,15,31
2	Mn2	17,23,15,17,18,18
3	Mn3	21,27,21,29,19,29

As can be seen in fig. 6, the actual speed with which mobile nodes are moving in WSN is visualized. The results for position RMSE obtained with the MM AUX-PF with an augmented state vector are shown in fig. 7.

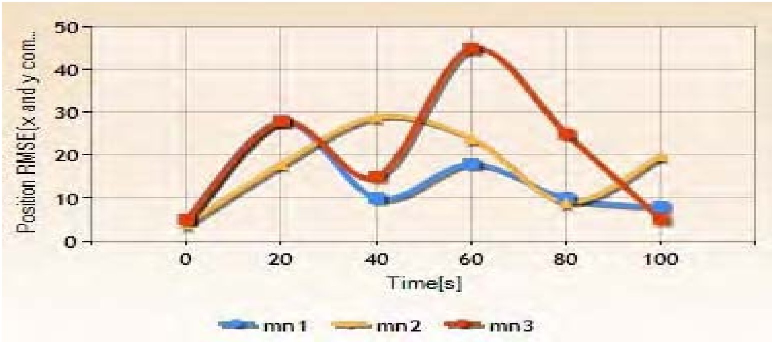

Fig. 7: Results for position RMSE obtained with the MM AUX-PF with an augmented state vector

As can be seen in fig. 7, it is evident that the position of the nodes over a period of time is shown in terms of x, y coordinates.

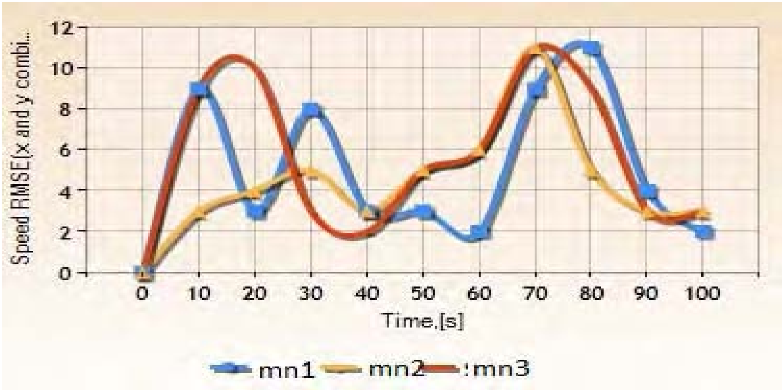

Fig. 8: Results of speed RMSE obtained with the MM AUX-PF with an augmented state vector

As can be seen in fig. 8, it is evident that the mobile nodes speed over a period of time is visualized and the speed is measures in m/s.

VI. CONCLUSIONS

In Wireless Sensor Networks, the problem of simultaneous location of mobile nodes with correlated in time measurement noise is solved by this paper. To solve the problem, two auxiliary filters are proposed. The first filter is with an augmented state vector while the second filter is with an artificial measurement. The simulations revealed that the proposed filters give high accuracy of location of mobile nodes. The proposed techniques can be used in real time applications like vehicle tracking, GPS etc.

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