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A survey on Indoor Localization Techniques in Wireless Body Area Sensor Networks

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ABSTRACT

Accurate location tracking is One of the major issues in Wireless Body Area Sensor Networks (WBANs). There are several techniques for indoor and outdoor environments to locate a person. This paper compares the performance of indoor localization schemes for optimal placement of wireless sensors in an area where, location tracking in required. In this paper, we investigate the performance of Particle filtering and Kalman filtering based location tracking techniques using Bays algorithm, in terms of localization accuracy is presented. Results show that particle filtering performs well in nonlinear and non-Gaussian environments. However, Bays algorithm is not considered the effect of noise in location tracking. For a noisy environment, We compare the results of Hidden Markov Model (HMM) and Bays algorithm. Results show that HMM outperforms Bays algorithm in terms of location estimation.
INDEX TERMS— Localization, WBAN, Kalman filtering, Particle filtering, Hidden Markov Model.

1. INTRODUCTION

With development of wireless devices and wireless communication in medical industry, research on WBAN attains significant attention. To provide a smart healthcare system, WBAN consists of low power and small wireless bio sensors implemented on human body. These sensors collect information from the human body and send to medical server placed in hospital to treat patient by a concerned person. The inherent characteristics of these sensor networks make localization an important issue in WBAN. Localization identifies position of target sensor nodes in a randomly distributed network. To assign measurement for location each node determines its own position.

Location tracking is measured through different location schemes. These schemes are classified into Range-free and range-based schemes. Range based schemes receive location information based on Time Of Arrival (TOA), Received Signal Strength (RSSI), Time Difference of Arrival (TDOA) and Angel Of Arrival (AOA). After determining range information each node estimates its location from these information. Range-based schemes earn higher accuracy than range free for location tracking in various environments. However, major drawbacks conclude that these information corrupted by noise and fading, therefore require additional devices for measuring range information. In Range-free schemes, unknown nodes use relative connectivity information from anchors for location estimation. These schemes employ range information based on Approximation Point In Triangle (APIT), Centriod and Distance Vector Hop (DV-Hop). Range-free schemes do not require additional devices for measuring range information. Therefore, these schemes are less effected by environmental changes than Range based schemes.

In this paper, we analytically survey various localization techniques. In indoor environments, it is difficult to predict path loss due to multipath and shadowing. Signal are effected due to scattering, reflection and diffraction and as well as by changing indoor environments like motion of peoples inside building.

The rest of the paper is organized as: Section II, discusses related work, section III, compares the performance of several localization schemes and section IV, concludes our research work.

2. MOTIVATION

Need of location tracking in WBAN is essential for patient moving in indoor and outdoor environments. In recent advancements, several localization schemes are adopted, keeping eyes on application requirement and demand to locate a person in WBAN.

In [1] O.Rehman, et al., compare the performance of several indoor and outdoor location tracking schemes. Their results show that particle filtering using Bays algorithm performs well in indoor environment without considering the effect of noise due to multipath fading in WBANs.

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Particle filtering based localization algorithm is used Bayesian Posterior probabilistic distribution method to estimate unknown node location. Time series location information is expressed by evaluation of particles [3].

Kalman filtering estimates the position of a person in linear systems and when the Probability Density Function (PDF) is Gaussian distributed. It estimates the location of person based on past, future and present states. It has prediction and correction steps for location tracking of a person, as discussed in [4].

In indoor localization techniques, we compare results in terms of localization accuracy. For nonlinear systems results show, particle filtering technique outperforms kalman filtering. Further, we compare Bayesian algorithm with HMM in noisy environment. HMM model outperforms Bayesian approach in terms of accurate localization estimation.

In [1], our previous work deals with indoor localization schemes without the considering the effects of noise. Noise such as multi-path fading is an important factor to generate error in localization process. In this work, we compare the Bays algorithm with HMM.

3. Indoor Location Tracking Techniques

In indoor environments, it is difficult to predict path loss. This is because of multi-path and shadowing. Signals are effected due to scattering, reflection, diffraction and by change in environment, like motion of peoples inside building. In this paper, we compares, Particle filtering and Kalman filtering using Bayes algorithm and HMM model.

3.1 Location Finding through Particle Filtering

In [3], Particle filtering based localization algorithm is proposed. Particle filters mostly used in non-linear systems. This algorithm receives RSSI information using beacon messages from its neighbors to infer its position. It uses finite random particles for sampling Probability Density Function (PDF). Bayesian Posterior probabilistic distribution method is used to estimate unknown node position. The inference of time series location information is expressed by the evaluation of particles. In the weighting phase of particle filter, we evaluate the likelihood of the particles. The most unlikely particles will be replaced by most likely ones, particles coverage focus a point step by step. We discuss three models for location tracking in particle filtering. These are target model, sensor model and observation model.

a) 3.1.1 Target Model

The target in the data is modeled as Binary Markov Process. The target presence variable, P_t, can take on two values; normaly $P_t = 0$ indicating the absence of target. $P_t = 1$, indicates presence of target. At any instant, target can present at any point. Disappearance of target means that intensity of target signal strength goes down below Threshold level (μ). We propose transitional probabilities of target initialization and target outage probability P_{out}: this probability is modeled as follows:

$$P_{int} = P_r(P_t = 1 \mid P_t - 1 = 0) \tag{1}$$

$$P_{out} = P_r(P_t = 0 \mid P_t - 1 = 1) \tag{2}$$

$P_{int} = 1$ will occur when $P_r > \mu$.

Target Model (Algorithm)

$$\textit{Transitional Probability} \leftarrow \textit{states } p(T)$$

$$\textit{Probability at any instant} \leftarrow \textit{states } p(t)$$

if

$p_{(t-1)} == 0$ and $p(t) == 1$ then $P_{(T)} = 1$

$P_{(int)} = 1$ "*target is present*"

end if

if

$P_{(t-1)} = 1$ and $p_{(t)} = 1$

then

$p_{(int)} = 0$ and $p_{(out)} = 1$ "*target is absent*"

endif

b) 3.1.2 Sensor Model

In [4], sensor model is described in detail. System of "N" small devices deployed over an area in an attempt to sense a signal are transmitted by the target. Placing of anchors can either be regular pattern or deployed in ad-hoc manners. The binary decision is made at each instant "t" on the basis of "M" samples of received signals. At a particular instant "t", each sensor can either be active or inactive. Each active sensor makes a binary decision about presence and absence of target.

Energy per sample of a target at i^{th} sensor in [4] is computed as:

$$E_T^2(d_i) = E_{To}^2 / d_i^2 \tag{3}$$

where, E_{T0}^2 specifies energy per sample of target signal at a distance of 1 unit and d_i denotes distance between target at i^{th} sensor.

Each sensor performs an assumption test between A_o (target absence) and A_1 (Target presence) assumption model. A_o indicates that energy received from target is negligible and target is apart from the sensor. Thus under A_o, "G" is Gaussian Vector, whose elements are independent with variance σ_n^2. Similarly, A_1 indicates that energy is received from target is significant and target is closer to the sensor. Under A_1, G is Gaussian Vector whose elements are independent variance $\sigma_N^2 + E_N^2(d_i)$ in [4]. It is given as:

$$A_0 = \sigma_N^2 \tag{4}$$

$$A_1 = \sigma_N^2 + E_N^2(d_i) \tag{5}$$

$$P(y:A_1) = \frac{1}{\sqrt{2\pi[\sigma_N^2 + E_N^2(d_i)]}} e^{-\frac{y}{2(\sigma_N^2)+E_N^2(d_i)}} \tag{6}$$

$$P(y:A_0) = \frac{1}{\sqrt{2\pi\sigma_N^2}} e^{-\frac{y}{2(\sigma_N^2)}} \tag{7}$$

We propose conditional probability that event A_0 occurs:

$$P(y;A_0 \mid y;A_1) = \frac{P(y;A_1 \times y;A_0)}{P(y:A_1)} \tag{8}$$

Applying conditional probability that event A_1 occurs:

$$P(y;A_1 \mid y;A_0) = \frac{P(y;A_0 \times y;A_1)}{P(y:A_0)} \tag{9}$$

Sensor model (Algorithm)

N = number of devices deployed in regular or adhoc manners

$$t\ states \leftarrow time\ instant$$

$$d_i\ states \leftarrow distance\ between\ target\ and\ i_{th}\ sensor \quad Mstates \leftarrow Samples\ of\ received\ signals$$

$$Energy\ per\ sample\ of\ transmitted\ signal \leftarrow E_{t_0}^2$$

Energy received per sample of target at i^{th} sesor is $E_N^2(d_i) = \dfrac{E_{t_0}^2}{d_i^2}$

$$target\ absence \leftarrow states(A_0)$$

$$target\ presence \leftarrow states\ (A_1)$$

if

$$A_1 = \sigma_N^2 + E_N^2(d_i) \quad \text{"}target\ is\ present\text{"}$$

else

$$[\ A_1 = \sigma_N^2\ ]\ \ target\ is\ absent$$

$$Applying\ condition\ probability \quad P(y;A_0 \mid y;A_1) = \frac{P(y;A_1 * y;A_0)}{P(y:A_1)}\ \ where$$

$$P(y:A_1) = \frac{1}{\sqrt{2\pi[\sigma_N^2 + E_N^2(d_i)]}} e^{-\frac{y}{2(\sigma_N^2)+E_N^2(d_i)}}\ \ and\ \ P(y:A_0) = \frac{1}{\sqrt{2\pi\sigma_N^2}} e^{-\frac{y}{2(\sigma_N^2)}}$$

$$P(y;A_1 \mid y;A_0) = \frac{P(y;A_0 * y;A_1)}{P(y:A_0)}$$

$$P(y;A_1 \mid y;A_0) \leftarrow states\ probability\ of\ A_1\ occurance$$

c) 3.1.3 Observation Model

The number of active sensors determines the size of observation vector. Vector Z_k contains binary observations from each active sensor at a given time k. If target is not detected, then corresponding element of z_k becomes 0, otherwise, 1.

Probability distribution of single node in [4] is moded as:

$$p(z_k(i) \mid x_k) = [P_D(di)]^{z_k(i)}[1 - P_D(di)]^{1-z_k(i)} \tag{10}$$

The probability distribution of vector z_k in [4] is given as:

$$p(z_k(i) \mid x_k) = \prod_{i=1}^{n}[PD(di)]^{z_k(i)}[1 - PD(di)]^{1-z_k(i)} \tag{11}$$

3.2 Kalman Filtering

Kalman filters are mostly used in linear systems, however, these systems are very few in numbers in the world. priori and posterior probability distribution of Kalman filter is Gaussian. Bayesian Probability distribution process helps to model the kalman filter. This PDF is discussed below:

d) 3.2.1 General Bayesian Tracking Model

Motion of a person modeled using general bayesian tracking model in [4] as follows:

$$x_k = f_k(x_{k-1}, u_{k-1}, w_k) \tag{12}$$

$$z_k = h_k(w_k, u_k, v_k) \tag{13}$$

Current location of person modeled by a non-linear function f_k, which depends on the previous location. h_k is a non-linear observation function. Current location of person can be estimated at each step recursively with update and prediction stage.

3.2.2 Prediction Stage

In [4], prediction stage is modeled as:

$$p(x_k \mid z_{1:k-1}) = \int p(x_k \mid x_{k-1})\, p(x_{k-1} \mid z_{1:k-1})\, d_{x_{k-1}} \tag{14}$$

e) 3.2.3 Update Stage

In [4], "m" update stage is modeled as:

$$p(x_k \mid z_{1:k}) = \frac{p(z_k \mid x_k)\, p(x_k \mid z_{1:k-1})}{p(z_k \mid z_{1:k-1})} \tag{15}$$

$$p(x_k \mid z_{1:k-1}) = \int p(z_k \mid x_k)\, p(x_k \mid z_{1:k-1})\, d_{x_k} \tag{16}$$

If observation and process noise are assumed to be Gaussian then general filtering reduces to a Kalman filter.

f) 3.2.4 Kalman filter

Kalman filter is optimal location estimator with Gaussian environments for linear systems. Square of error is stored between estimated state and true state for many runs of kalman filter at a particular instance. At that instance, Mean Square Error is closely matches the Kalman gain assigned at that instance. Kalman filters measurement equations in [4] are as follows:

$$x_k = f_k x_{k-1} + w_k, w_k : N(0,Q), X(0) : N(X(0),V(0)) \tag{17}$$

$$Z_K = H_k x_k + v_k, v_k : N(0,R) \tag{18}$$

The measurement and process noise are defined covariance matrix Q and R and is assumed to be independent. The prediction and update stage of Kalman filter is given by following equations from [4] is:

g) 3.2.5 Predict stage for Kalman filter

$$Z_k^{\wedge} = F_{x_k^{\wedge}-1}, \tag{19}$$

$$Z_k^{-} = F_{p_{k-1}} F^T + Q, \tag{20}$$

h) 3.2.6 Update stage for Kalman filter

$$k_k = p_k^{-} H^T (HP_k^{-} H^T + R)^{-} 1 \tag{21}$$

$$x_k^{\wedge} = x_k^{-} + K_k (Z_k - H_{xk}^{\wedge} -) \tag{22}$$

$$P_k = (1 - k_k H) p_k^{-} \tag{23}$$

Initially current location is predict using previous location. The estimations are updated using weighted observations by the Kalman gain (k_k). If the variance is high, process noise variance matrix "R" becomes large, thus decreases Kalman gain and effects observation. Kalman gain becomes small, if posteriori error variance p_k is low, it gives more significance results to the predictions.

Simulation results for particle and kalman filters

All simulations are performed in MATLAB. Reason behind selection this tool is necessary matrix operations are implemented to program Particle filter and Kalman Filter.

All simulations are performed for the case, where initial state is known and true state of target is provided to the filter. In our case 50 particles are used and senors are randomly distributed. Fig. 1(a) shows probability distribution function at a specific time interval in discrete and continuous manners for particle filter. In fig. 1(b), we compare location estimation of particle filter and kalman filter. We suggest that in a random, nonlinear systems and even for non-Gaussian systems, Particle filter is best suited among all of four location tracking techniques discussed for indoor environments. Kalman filter is optimized for linear systems only and not work efficiently for non linear systems. Particle filter is accurate location tracking technique. However, it implies greater computational overheads, which is a major drawback.

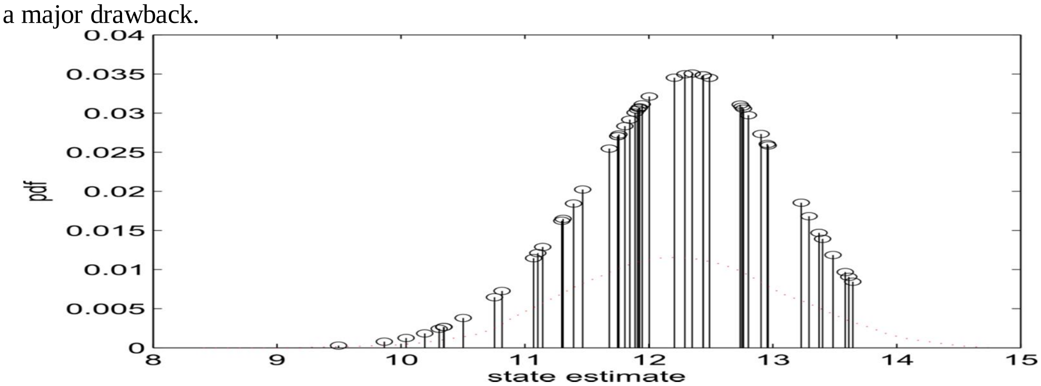

Fig. 1(a) [PDF For particle filter at Specific Time]

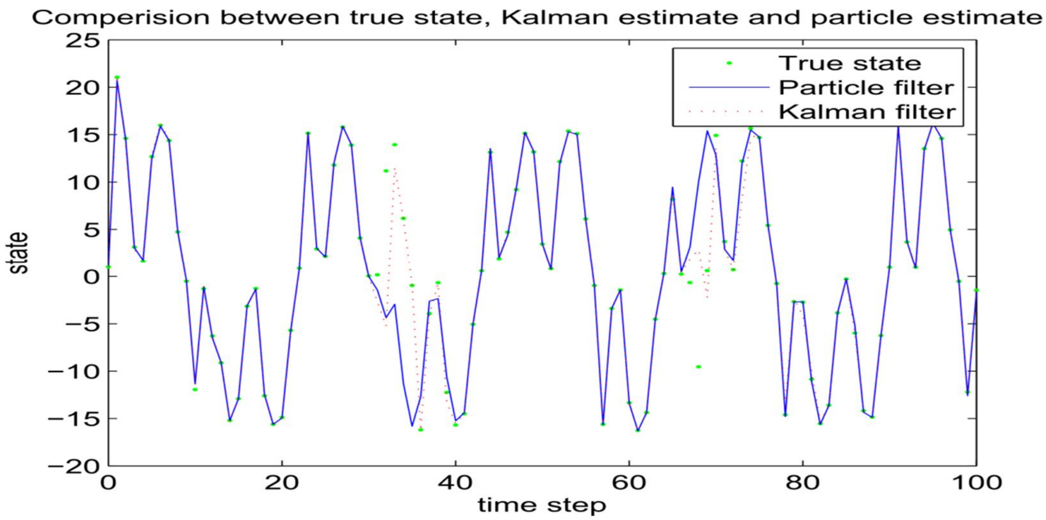

Fig. 1(b) Error Estimation Through Particle Filter and Kalman Filter

Fig. 1 Location Tracking Through Particle and Kalman Filter

2. 3.4 Hidden Markov Model for location tracking

This section presents, Hidden markov localization algorithm to estimate location of sensors. The reason behind, choosing of this algorithm over bayes method to modelize noisy signals; a lower ratio of noise leads to lower error estimation. HMM model shows how states are relate to actual observations of a person. Reason of using HMM localization process because it can model sequential states. The states are hidden, only observe sequence of observations, which are generated from sequence of states.

In our case, observations are hidden nodes, assume that they are generated by Gaussian PDF from the states. In BAN localization, there are two types of observation error sources. Non Gaussian and Gaussian component. The gaussian component is observed from two sources: Unbiased zero mean Gaussian component, mitigated by averaging several consistence measurements and biased Gaussian components achieved by RSSI sensitivity model.

The non-Gaussian component which are caused by LOS obstacles and multi-path reflections. Sensing model is modeled in [5] as:

$$RSSI_{ij} = f(\| X_i - X_j \|, P_j) + (e_{GFreeSpace+e_{LN}})ij \tag{24}$$

In this equation, $\| X_i - X_j \|$ is euclidean distance between node i and j, e_{GFree} is Gaussian error in terms of free space transmission and e_{LN} is non-Gaussian error source caused by log-normal fading. R_{ij} is probability distribution of measured RSSI of receiver i from transmitter j, which gives true distance d and transmission power p_j of the transmitter j is given in [5] as:

$$p_{GS}(r_{ij} \mid d_{ij}, p_j) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{(r-r_{exp})^2}{2\sigma}} \tag{25}$$

where, true distance d_{ij} and transmission power p_j are obtained from the transition models and replaced by estimated distance d'.

A HMM is recognized by following elements.
N : number of hidden states
M : number of symbols
A : state transition matrix A. $A_{ij} = P(qt+1 = j \mid qt = i) 1 \le i, j \le N$
B : observation probability distribution. $B_j(k) = P(O_t = k \mid q_t = j) 1 \le k \le N$
π : The initial probability distribution: $\pi_i = p(q_1) = i) 1 \le i \le N$

λ : the entire model $\lambda = (A, B, \pi)$

Knowing the estimation of Anchor nodes is considered as initial state sequence (π). From initial position, node movement takes place from semi markov mobility model and those probabilities from the transition matrix A. The hidden state sequences (nodes) are localized by the observation matrix B.

In [6], there are three problems that must be solved for making HMM model useful in real world applications.

3.41. The evaluation problem

In a model, $\lambda = (A, B, \pi)$ and a sequence of observations $O = o_1, o_2, ..., o_T, po \mid \lambda$ needs to be found. The calculation method with considerably low complexity that uses an auxiliary variable is:

$$\alpha_t(i) = p(0_1, 0_2, ...0_t, q_t = i \mid \lambda) \tag{26}$$

With $\alpha_t(i)$ is called forward variable, and $o_1, o_2, ..., o_T$ is the partial observation sequence. So, the required probability is given in [6] as :

$$p(o \mid \lambda) = \sum_{i=1}^{N} \alpha_t(i) o_{ij}, 1 \le j \le N, 1 \le t \le T-1 \tag{27}$$

$$p(o \mid \lambda) = \sum_{i=1}^{N} \alpha_t(i) \tag{28}$$

This method is commonly known as forward algorithm.

The backward variable $\beta_t(i)$ can be defined in [6] as:

$$\beta_t(i) = p(o_{t+1}, o_{t+2}, ..., o_t \mid q_t = i, \lambda) \tag{29}$$

These two ways can be used to calculate $p(o \mid \lambda)$, either using forward or backward variable:

$$p(o \mid \lambda) = \sum_{i=1}^{N} p(0, q_t = i \mid \lambda) = \sum_{i=1}^{N} \alpha_(i) \beta_t(i) \tag{30}$$

3.4.**2. The Decoding problem**

By using viterbi algorithm, whole state sequence is found with most likely sequence. Viterbi algorithm is a dynamic programming algorithm to find the Viterbi path that is hidden in the observed sequence. The Viterbi path can also be regarded as the most likely sequence of hidden states. Assume, to be the probability of the most probable path to the state. Assume γ is probability of the most probable path to the state. Then $\gamma_t(i)$ is the maximum probability of all possible sequences ending at state "i" at time "t". "A" is the matrix of state-transition probabilities with elements "a_{ij}", "B" is the matrix of observation probabilities with elements "b_{ij}" is modeled in [6] as:

$$\delta_t(i) = max_{q_1, q_2, .., q_{t-1}} (q_1, q_2, .., q_{t-1}, q_t = i, o_1, o_2, ..., o_{t-1} \mid \lambda) \tag{31}$$

$$\delta_{t+1}(j) = max_t [\delta_t(i) a_{ij}] b_j [o_{t+1}] \tag{32}$$

Initialization

$$\delta_i(i) = \pi_i b_i(o_1), 1 \le i \le N \tag{33}$$

$$\phi_i = 0 \tag{34}$$

Recursion

$$\delta_t(j) = Max_{i<1<N} [\delta_{t-1}(i) a_{ij}] b_j(o_t) \tag{35}$$

$$\phi_t(j) = Max_{i<1<N} [\delta_{t-1}(i) a_{ij}] 2 \le t \le T, 1 \le j \le N \tag{36}$$

3.4.3 The learning problem

How should we adjust the model parameters A, B, π in order to maximize $po \mid \lambda$, where at amodel λ and a sequence of observations $o = 0_1, o_2, ..., o_T$ are given?

This problem can be solved by using Baun-Welch algorithm.

For transition and emission probabilities, this algorithm computes the maximum likelihood estimation, when emission is given as training data only. The algorithm has two steps.

1. For each HMM state, calculate forward and backward probability.
2. The probabilities of whole observation sequence is multiplied to calculate transition emission pair values.

Suppose a person is in position "i" at time $"t"$ and position "j" at time $"t+1"$ is modeled in [6] as:

$$\xi_t(i,j) = \frac{p(q_t = i, q_{t+1} = j, o \mid \lambda)}{p(o \mid \lambda)} \tag{37}$$

$$\xi_t(i,j) = \frac{\alpha_t(i) a_{ij} \beta_{t+1}(j) b_j(o_{t+1})}{\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_t(i) a_{ij} \beta_{t+1}(j) b_j(o_{t+1})} \tag{38}$$

γ_t is the probability that a node is in state "i" at time "t", given the observation sequence

$$\gamma_t(i) = \sum_{j=1}^{N} \xi_t(i,j) \tag{39}$$

$\sum_{t=1}^{T} \gamma_t(i)$ is expected number of times a state i is visited.

$\sum_{t=1}^{T-1} \xi_t(i,j)$ is the number of transitions from state i to j.

Baun-Welch update Rule:

π_i = expected frequency that in state i at time $t = 1$ $= \gamma_1(i)$.

a_{ij} is the (expected number of times in state j and observing symbol k) / (expected number of time in state j).

$$a_{ij} = \frac{\sum_{t=1}^{T-1} \xi_t i, j}{\sum_{t=1}^{T-1} \gamma_t(i)} \tag{40}$$

$b_j(k)$ is the (expected number of times in state "j" and observing symbol k) / (expected number of time in state j)

$$b_j(k) = \frac{\sum_{t, ot=k} \gamma_t(j)}{\sum \gamma + (j)} \tag{41}$$

a) Simulation Results

The proposed work is implemented using MATLAB to validate and evaluate performance of HMM based localization. The Bayesian and HMM based location scheme estimates the location at 100 time instants, when log normal fading channel is introduced. For a particular time instance, square of error between true state and estimated state is measured. Results show that HMM outperforms Bayes filtering in terms of location estimation. Location estimation error of Bays filtering is significance because of noise. Fig 2(a), shows location tracking Separately for Bayes filtering and HMM. Fig 2(b), shows combine location estimation of Bays filtering and HMM.

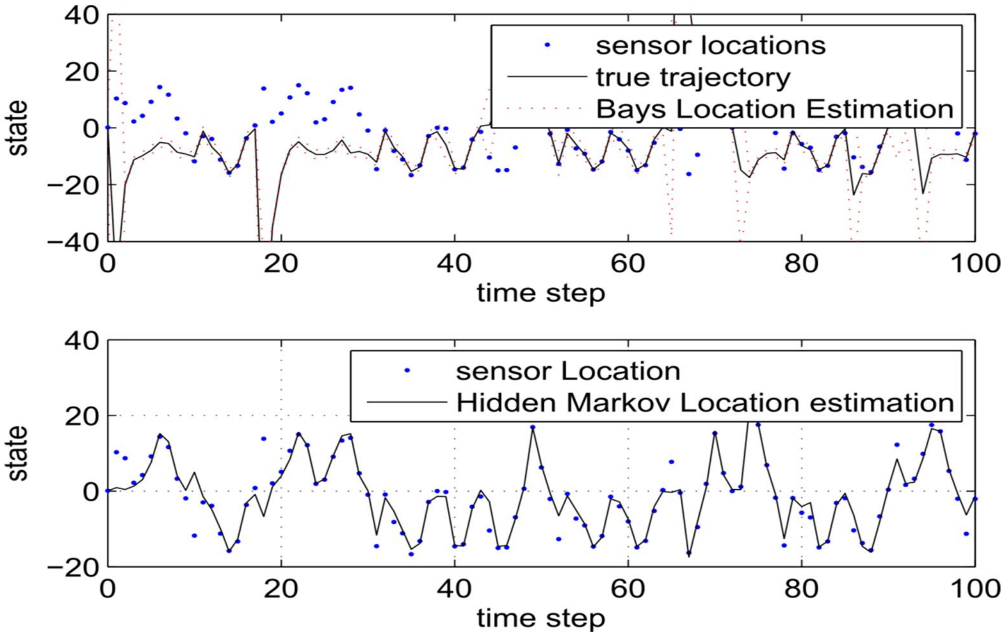

Fig. 2(a) Location estimation using Bayes filtering and Hidden Markov Model

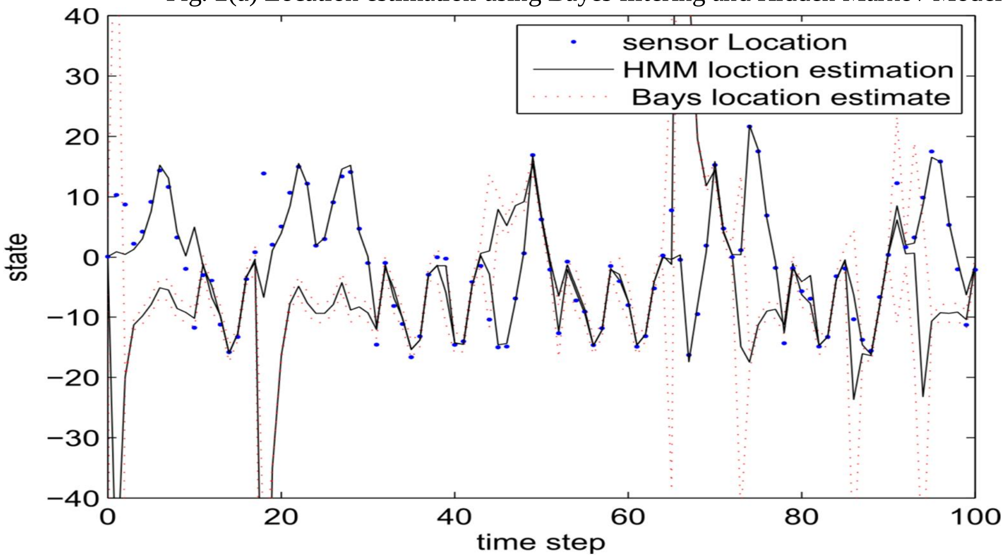

Fig. 2(b) Combine results, location estimation through Bayes filtering and Hidden Markov Modeling

Fig.2 Comparison of Location tracking using Bays and Hidden markov model

4. CONCLUSIONS and FUTURE WORK

In this paper, we compare several localization schemes for indoor environments in WBAN. Our results show, particle filtering performs well in nonlinear systems for indoor environments. We also compare the Bayes algorithm and HMM location tracking scheme in the presence of log-normal fading. HMM outperforms Bayes algorithm in terms of location accuracy.

In WSNs, due to small battery power, we are interested in energy efficient location tracking as energy efficency is achieved through various routing schemes as proposed in [13-18]. Our objective is to enhance the life time of a sensor netwrok. Hence, applications like data gatering, data processing, data sensing and location tracking should be energy efficint.

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