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# Object Tracking in Wireless Sensor Network based on the mixture of Kalman Filter and Probability based Model

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***ABSTRACT:*** *Wireless Sensor Networks (WSNs) consists of large number of sensor nodes which are capable of sensing and processing by using the computational power. Object tracking is one of the important applications in WSN.Extended Kalman Filter (EKF) is the most widely used method for object tracking and Kalman filter for estimating the state of the object. Tracking is difficult because sensors have to be send data to the head sensor from other sensors with same time instants. Maximum Likelihood Estimation (MLE) is used to solve the data association problem but it gives localization error. In this paper, a new approach probability based estimation model is proposed to provide superior performance in combination with Kalman Filter (KF).*

***INDEXTERMS:*** *Wireless Sensor Networks (WSNs, Object Tracking, Extended Kalman Filter, Kalman Filter, Bayesian estimation model.*

## I. INTRODUCTION

Wireless Sensor Networks (WSNs) consists of large number of small, low power, and inexpensive sensor nodes with on board sensing, processing, and wireless communication capabilities the sensors are spatially distributed to monitor the conditions at different locations. Target tracking is one of the active area in WSNs and is used to collect data from the environment consists of large number of sensor nodes and one or more base stations. The nodes have the capability to sense the data, process data and send it to rest of the nodes or to the base station and the nodes are connected through wireless communication channels. Tracking is one of the challenging applications and is managed by the master node. The main thing is that WSNs are first developed for military applications but now it is used for wide variety of applications among which target tracking is one of the canonical application. In tracking of a single object more number of densely deployed sensors measure and estimate the state of the object. The state indicates position, velocity and heading of the object. In tracking of multiple objects the WSNs are given the work to gather information from sensor nodes at each timestamp. Existing acoustic source localization methods make use of three types of physical measurements: time delay of arrival (TDOA), received signal strength (RSS), direction of arrival (DOA).DOA can be estimated by making use of the phase difference measured at receiving sensors and it is applicable when the acoustic source emits narrowband signal.TDOA is mostly used for broadband acoustic source localization. Target tracking is one of the most important applications of WSNs, in which, due to the limited resources for sensing, communication, and computation, the network must rely on sensor management to balance the tracking accuracy and energy consumption [3].

In multiple target tracking, the sensors are capable of obtaining more than one measurement; these measurements are not only generated by the objects but also possibly from the distributed heap. Hence multiple targets tracking algorithm needs to solve the data association problem, i.e. correctly mapping the measurement and target pairs with the interference introduced by the mass of objects. Extended Kalman Filter (EKF) is the most widely used method for target tracking. The EKF simply linearizes all nonlinear transforms. Also it has some limitations that linearized transformations are reliable only if the error propagation is well approximated by a linear function and the resulting state diverges [5].In this paper the distance measurements are considered. Moreover for tracking multiple objects which are not sufficiently separated temporally and spatially in the sensor field, may also lead to unlabelled measurements in the sensor data. This uncertainty in measurement leads to the well known data association problem.Kalman filtering is the powerful framework for solving data association problem and has better accuracy and consistency than EKF [5].

To overcome the drawback of EKF many measurement conversion methods are used to transform the non linear measurements into linear ones. Maximum Likelihood estimation which is a measurement conversion method is proposed in this paper which resolves the data association problem and then applying standard kalman filtering which then updates the state (position and velocity) of the object. The kalman filter is the optimal state estimator for unconstrained linear systems subject to normally distributed state and measurement noise which are used in widely for tracking applications. The KF as an application of Bayes' rule under the assumption that all estimates have independent, Gaussian-distributed errors. This has lead to a common misconception that the KF can only be strictly applied under Gaussianity assumptions [4].

## II. SYSTEM MODEL

Here, the tracking of multiple moving objects in a sensor field is considered. When the object is moving through the sensor area where sensors are located will detect the object and then form a cluster [1]. From this cluster one of the sensor nodes is selected to be the leader sensor which serves as the center. In target tracking applications, at each time stamp, measurements obtained from numerous sensing nodes need to be transmitted to the cluster head. The sensor nodes have limited resources and there is a high probability that the data has some repeated information and such redundancy needs to be developed by the routing protocols to improve energy and bandwidth. After collecting all the information the leader sensor then report it to the sink or to the computer.

### *a) Tracking moving object model*

The object is considered to be moving in two-dimensional field. The position and velocity of the target at each time stamp is considered in x and y coordinates.

$$P_t = [\ P_x(t)\ \ V_x(t)\ \ P_y(t)\ \ V_y(t)\ ]^T$$

Where ($P_x(t)$, $P_y(t)$ are the position coordinates of the target along X and Y-axes at time $t_{t,}$ respectively, and ($V_x(t)$, $V_y(t)$) are the velocities of the target along X- and Y-directions at $t_{t,}$ respectively. The tracking is done in two phases monitoring and reporting and these two are interleaved to get the information.

### *b) Measurement Model*

The sensors are all considered to be same size [1].The distance measurement with respect to the target at specific time is noted. The true distance between the sensor and the target are calculated by using the known location of sensors. The measured distances collected from all the sensor nodes are then transferred to the leader sensor.

Let $s_i$ be the true distance between sensor i and the object, we have,
$S_i = \sqrt{}\ (p-p^i)^2 + (q-q^i)^2$, where ($p^i$, $q^i$) is the known location of sensor i,and (p,q) is the unknown position of the object at time $t_t$.

$$Z_i = (1 + ¥_i)\ Si + N_i = Zi + A_{i,}$$

$Z_i$ is the measured distance to the target by the sensor i at time $t_{t,\ ¥i}$ and $N_i$ are the additive and Multiplicative noises of sensor i.
Total noise of sensor i, denoted by $A_i = S_i + N_{i.}$

### *c) Maximum Likelihood Estimation (MLE)*

Maximum Likelihood Estimation (MLE) is the existing method used for data association problem. This method has two advantages first; the MLE method can able to handle more number of targets within the sensor field.MLE method provides higher accuracy in terms of source location estimates compared to the other methods. But also there are some drawbacks because of some assumptions that the distance between sensor and the object is very small which is not always true and also there will be delay in transmitting the measured distance to the data collecting node. so in order to reduce this delay a new approach is proposed in this paper which is a probability based method.

## III. PROPOSED SCHEME

### a) *Proposed Algorithm*

To overcome this problem, another measurement conversion method is suggested which is Bayesian estimation model. It is a probability based method which resolves the problem formulated by MLE.Bayesian estimation updates the probability density function of the object state through two stages: a prediction stage correction stage. In prediction stage the probability density function at the previous time stamp through the target dynamics form one step ahead prediction. In correction stage through bayes' rule and form new probability density function at current time stamp.

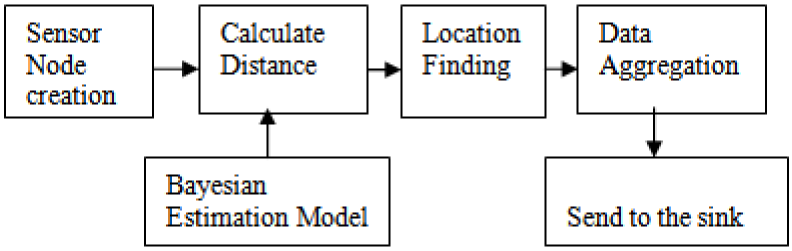


Fig.3.Block Diagram of the proposed scheme.

Fig.3 describes about the proposed scheme in which Bayesian estimation model is used for distance calculation. The algorithms within Bayesian estimation framework include kalman filter.Kalman filtering is a powerful framework for solving data assimilation problems.Kalman filter, which clearly has better accuracy and consistency than the extended Kalman filter (EKF).The basic idea is to transform the nonlinear measurement model into a pseudo linear form in the

Cartesian coordinates, estimate the bias and covariance of the converted measurement noise, and then use the Kalman filter, which clearly has better accuracy and Consistency [5].

***d) Kalman Filter***

Bayesian is followed by applying standard kalman filtering in order to update the state of the object recursively.Kalman filtering is a powerful framework for solving data assimilation problems.
Using Bayes rule, the posterior probability distribution of (x,y)[1],

$$P(x,y/Z)=[\ p(Z/x,y)p_a(x,y)] /\ p(Z)$$

$p_a$ (x,y) – prior probability function of (x,y) known by the sensor nodes. Kalman filter, which clearly has better accuracy and consistency than the extended Kalman filter (EKF).The basic idea is to transform the nonlinear measurement model into a pseudo linear form in the Cartesian coordinates, estimate the bias and covariance of the converted measurement noise, and then use the Kalman filter, which clearly has better accuracy and Consistency [4]. It is an optimal estimator that is it infers parameters of interest from inaccurate observations. It is so popular for its convenient form for online real time processing and easy to formulate and implement.

## IV. SIMULATION RESULT

The software used here is network simulator 2(NS-2), fig.4. describes the node creation in which sensor nodes are created and the corresponding position and energy are updated.

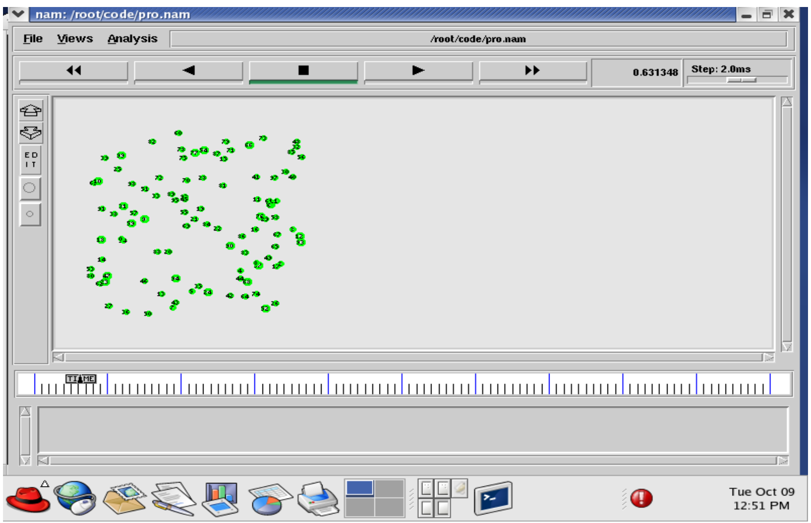


Fig.4. Node creation

Fig.4.describes the architecture models in which 100 nodes are generated.

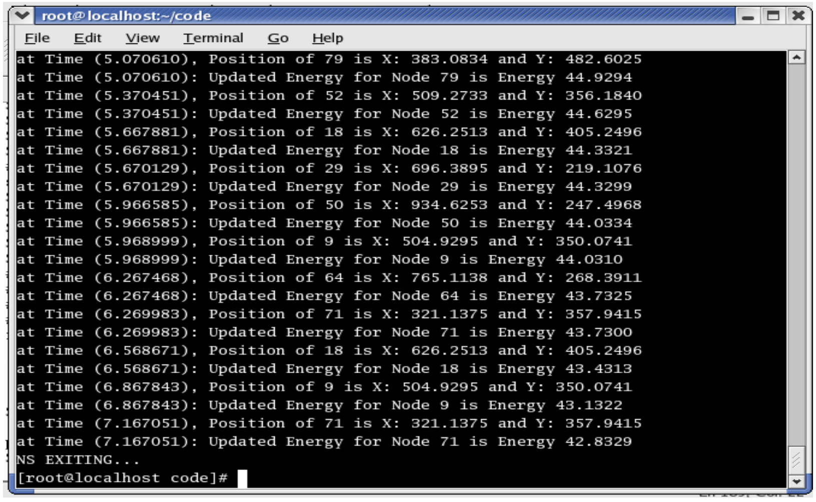


Fig.5.Node Position and Energy Updating Trace File for 100 nodes.

Each node's position and energy is updated, energy model is used for updating the energy of the node.

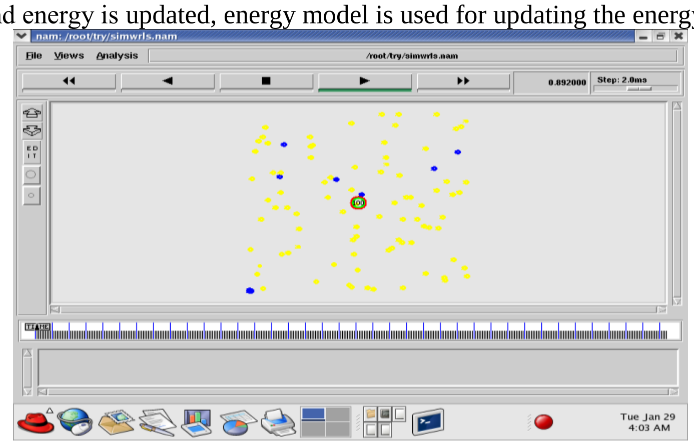


Fig.6. Monitoring Phase

In monitoring phase (fig.6.), the sensor nodes detect the object when the objects are moving within the sensor field. The blue color nodes indicate objects and sensor nodes are yellow in color before it starts sensing the objects.100$^{th}$ node is the data collecting node which gathers information from the sensor nodes.

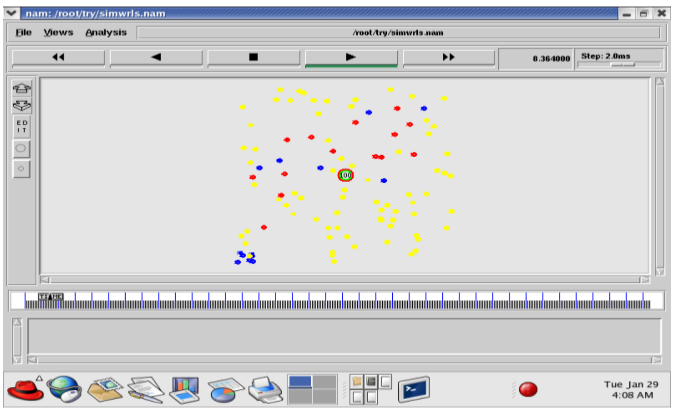


Fig.7.Reporting Phase

After the objects get detected the sensor nodes will then transmit this information (fig.7.) (i.e.) report the information to the leader sensor and the leader sensor then update the current position of the object and send it to the sink. The red color nodes indicate that the sensor nodes start sensing the object. After sensing the objects the sensors measure the distance of the objects and transmit this information to the data collecting node.

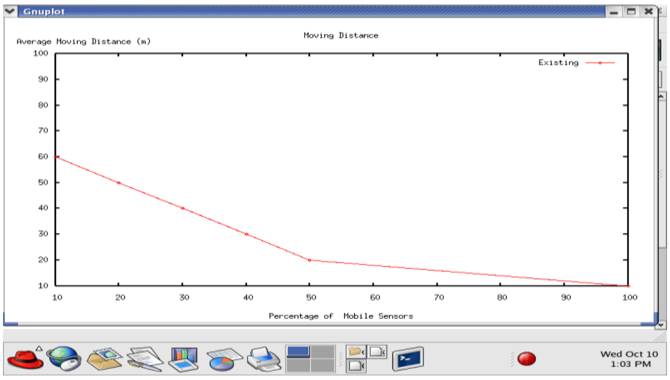

Fig.8.Moving Distance of the Object compared with the percentage of sensors.

Fig.8. describes if the percentage of sensor node increases then the distance between the node and the object will get reduced. If the sensors number is reduced then the distance between them increases and will introduce more localization error

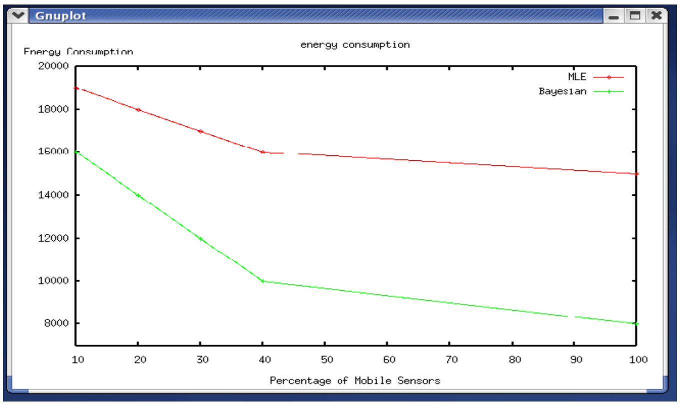

Fig.9. Energy Consumption Comparison for MLE vs Bayesian

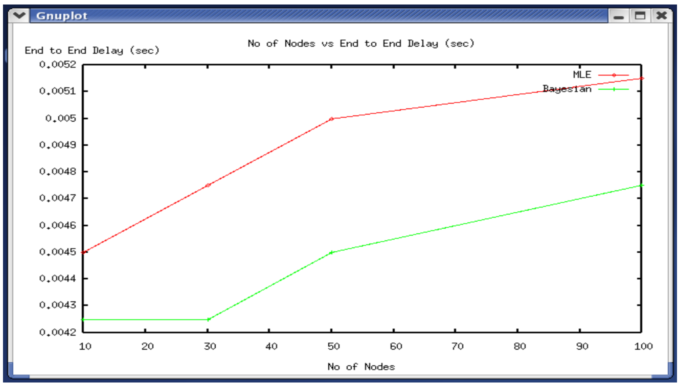

Fig.10.End to end delay Comparison for MLE and Bayesian.

## V. CONCLUSION

This work proposes probability based most probable Bayesian estimation model which is a measurement conversion method. The reason for measurement conversion is that the EKF need to transform its nonlinear state measurements into linear form, which resolves the data association problem. The Existing MLE has a problem of delay in transmitting the measured distance to the user.Our proposed approach has the advantage of reducing this delay in transmitting the information.

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