Multiple Object Tracking in Wireless Sensor Network based on the Mixture of KF and MLE

P.Ganeshwari
PG Student
Dept. of ECE., Kalasalingam University,
Krishnankoil, Virudhunagar Dist, Tamil Nadu, India

S.Diwakaran
Assistant Professor
Dept. of ECE., Kalasalingam University,
Krishnankoil, Virudhunagar Dist, Tamil Nadu, India

ABSTRACT

Wireless Sensor Networks (WSNs) has wide variety of applications and object tracking is one among that applications. In this paper, tracking of multiple objects is considered. The Extended Kalman Filter (EKF) algorithms are mostly used to get a linear form from the nonlinear states and then applying the standard Kalman filter for updating the state estimate. However, a significant drawback of the EKF algorithms is that the resulting estimation of the state diverges from its original state in many applications. In order to solve this problem one measurement conversion method Maximum Likelihood Estimation (MLE) is proposed in this paper. The analysis is based on object tracking in multiple sensor system. The object tracking is difficult because sensors have to be send data from other sensors to the head with same timestamps. This is the well known data association problem and a method which is combination of Kalman Filter (KF) and Maximum Likelihood Method is proposed to solve this problem.

Keywords

Wireless Sensor Networks (WSNs), Object Tracking, Extended Kalman Filter (EKF), Kalman Filter (KF).

1. 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 [2].

In multiple target tracking, a sensor node may acquire 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 [3].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 [4].

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

2. PROCESS 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 (fig.1). 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.

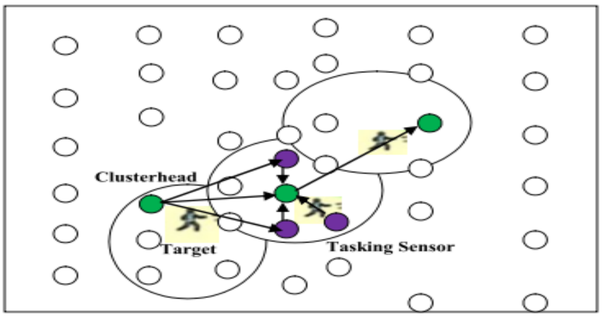

Fig.1.Object Tracking in Wireless sensor Network.

2.1) 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.

2.2) Observation 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.

The leader sensor then updates the current position of the object and transmits this information to the sink.

2.3) Maximum Likelihood Estimation

Maximum Likelihood Estimation (MLE) is the method used for data association problem. This proposed 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.

2.4) Kalman Filter

MLE is followed by applying standard kalman filtering in order to update the state of the object recursively.

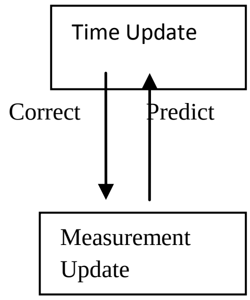

Fig.2.Kalman Filter Processing

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 [4].

3 PROPOSED SCHEME

3.1) 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 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

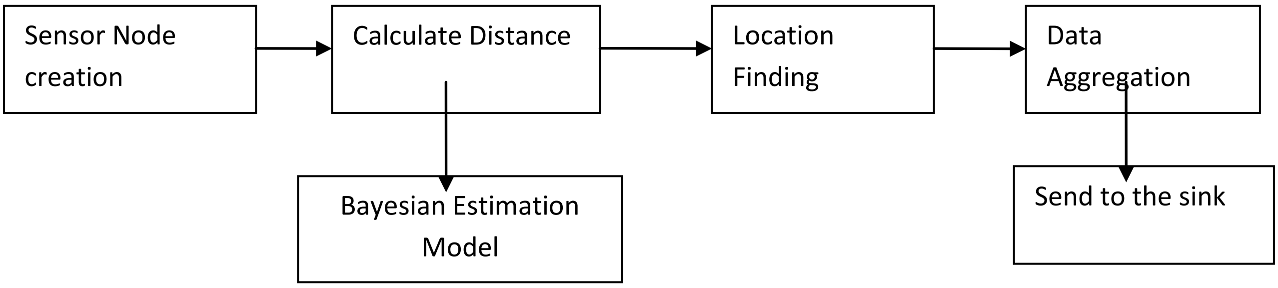

Fig.3.Block Diagram of the proposed scheme.

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4. 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.

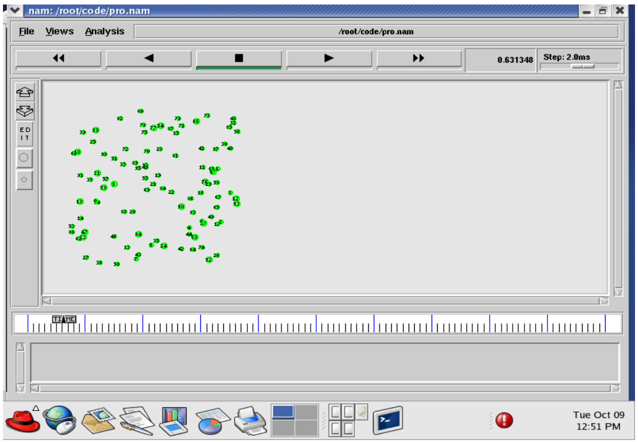
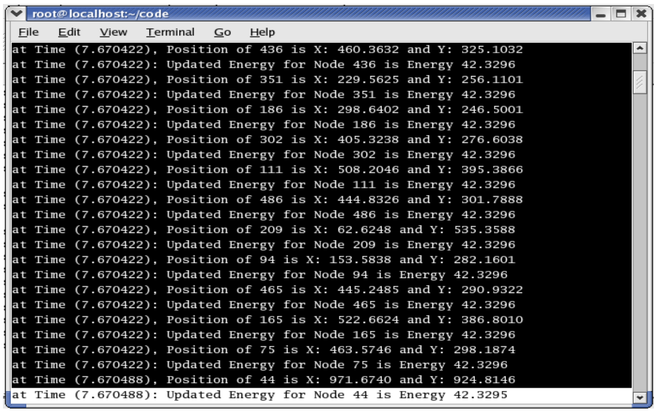


Fig.4. Node creation

Fig.4.describes the architecture model containing 100 nodes.



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at Time (7.670422), Position of 436 is X: 460.3632 and Y: 325.1032
at Time (7.670422): Updated Energy for Node 436 is Energy 42.3296
at Time (7.670422), Position of 351 is X: 229.5625 and Y: 256.1101
at Time (7.670422): Updated Energy for Node 351 is Energy 42.3296
at Time (7.670422), Position of 186 is X: 298.6402 and Y: 246.5001
at Time (7.670422): Updated Energy for Node 186 is Energy 42.3296
at Time (7.670422), Position of 302 is X: 405.3238 and Y: 276.6038
at Time (7.670422): Updated Energy for Node 302 is Energy 42.3296
at Time (7.670422), Position of 111 is X: 508.2046 and Y: 395.3866
at Time (7.670422): Updated Energy for Node 111 is Energy 42.3296
at Time (7.670422), Position of 486 is X: 444.8326 and Y: 301.7888
at Time (7.670422): Updated Energy for Node 486 is Energy 42.3296
at Time (7.670422), Position of 209 is X: 62.6248 and Y: 535.3588
at Time (7.670422): Updated Energy for Node 209 is Energy 42.3296
at Time (7.670422), Position of 94 is X: 153.5838 and Y: 282.1601
at Time (7.670422): Updated Energy for Node 94 is Energy 42.3296
at Time (7.670422), Position of 465 is X: 445.2485 and Y: 290.9322
at Time (7.670422): Updated Energy for Node 465 is Energy 42.3296
at Time (7.670422), Position of 165 is X: 522.6624 and Y: 386.8010
at Time (7.670422): Updated Energy for Node 165 is Energy 42.3296
at Time (7.670422), Position of 75 is X: 463.5746 and Y: 298.1874
at Time (7.670422): Updated Energy for Node 75 is Energy 42.3296
at Time (7.670488), Position of 44 is X: 971.6740 and Y: 924.8146
at Time (7.670488): Updated Energy for Node 44 is Energy 42.3295
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Fig.5.Node Position and Energy Updating Trace File for 100 Nodes.

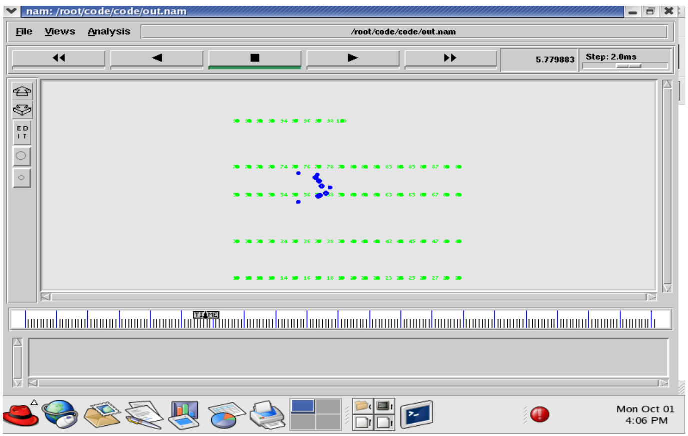

Fig.6. Monitoring Phase

In monitoring phase (fig.6.), the sensor nodes detect the object when the objects are moving within the sensor field

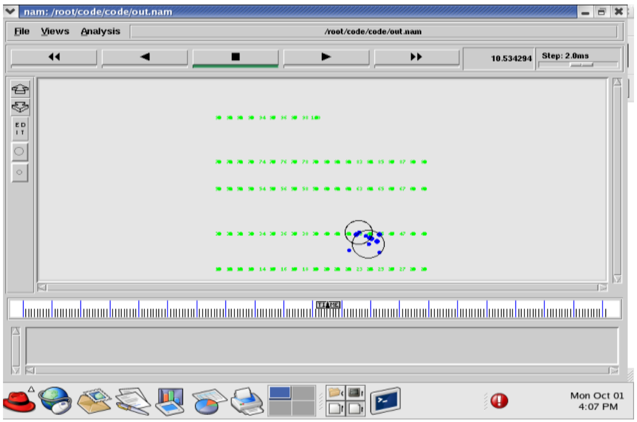

Fig.7.Reporting Phase

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.

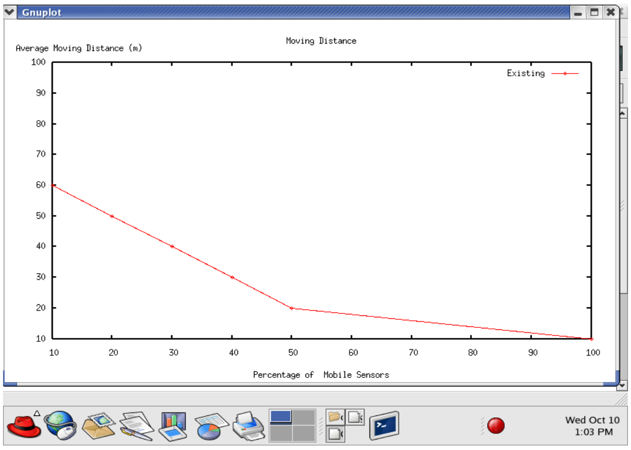

Fig.8.Moving Distance of the Object compared with the percentage of sensors.

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.

5. CONCLUSION

This paper proposed Maximum Likelihood Method, a measurement conversion method which resolves the data association problem but if the sensors are placed closely enough then the MLE algorithm gives localization error, if the sensors are thinly distributed then the error will be large [5],so in order to overcome this problem a new estimation model is needed.

6. FUTURE WORK

In the future work, probability based most probable Bayesian estimation model can be used which is one of the measurement conversion method. The reason for measurement conversion is that the EKF need to transform its nonlinear state measurements into linear form, so in order to overcome the problem of MLE, Bayesian estimation model is needed.

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