Prediction Based Object Recovery Using Bayesian Iterative Estimation

S.Pavalarajan, A.Vincent Antony Kumar

Abstract— There have been many researches carried out on Wireless Sensor Networks (WSN) in recent years because of its wide applications. Object tracking is one of the most common requirements in WSN applications. Object tracking is mainly used to track certain objects in its detection area and to report their location to the application users via base station, periodically. Prediction based tracking schemes has been followed here to achieve reductions in energy dissipation from the sensor nodes. Efficient detection and location estimation of the missing object are significant requirements of an Object Tracking in WSN. In this paper, the research is concerned with the problem of coordinate calculation of sensor nodes and objects to recover the missing objects in location estimation process, regardless of the specific estimation methods. In order to achieve significant reductions in energy dissipation, we propose Atomic Multilatertion, Collaborative Location Estimation and also we propose Iterative Bayesian Estimation Method to minimize location errors. The simulation results show that Bayesian estimation achieves good performance and it outperforms atomic multilatertion and collaborative location estimation in terms of energy efficiency and location errors.

Index Terms— Wireless Sensor Network, Object tracking, multilatertion, Bayesian estimation, Energy consumption, Location Error.

1 INTRODUCTION

A Wireless sensor network (WSN) typically employs low-cost, densely organized, tiny electronic nodes connected to each other via wireless communication. Each node is equipped with embedded processors, sensor devices, and storage and radio transceivers. WSNs have attractive commercial application in areas such as healthcare, object tracking, monitoring, smart homes, and surveillance and intrusion detection [1].WSN are created by deploying a large number of sensor nodes in a certain area, which is usually called the detection area, for monitoring purposes. Sensors are interconnected and are used collectively as a monitoring and reporting device to acquire precise types of data as desired by the application requirements[2].

Object tracking is one of the most demanding applications in WSNs due to its application requirements, and it places a heavy burden on the network resources, particularly in energy consumption. The main task of an Object Tracking is to track a moving object and to report its latest location in the monitored area to the application in an acceptable timely manner, and this dynamic process of sensing and reporting keeps the network's resources under heavy pressure [3]. Among the technical issues to be addressed in developing sensor networks for object tracking, energy conservation is probably the most critical one, since the sensor nodes are often supported by batteries which could be difficult to replace. A lot of existing researches are focused on optimizing the communication cost by inactivating radios as much as possible or by trading off computation for communication [4-5].

Prediction based tracking technique is an object tracking technique that revolves around the ability to predict the objects future movements and track it with the minimum number of sensor nodes while keeping the other sensor nodes in the network in sleep mode. This will lead to significantly reducing the networks energy consumption. Using prediction technique, it is possible to have some missing objects during the tracking process. The main contribution of the paper is to localize the missing object and to reduce the location error. For tracking, we adopt the framework proposed in [6].

The rest of this paper is structured as follows. We briefly review the related work in Section 2. In section 3.1 we describe the problem statement and the proposed work such as Atomic Multilatertion, Collaborative Location Estimation and Bayesian Estimation presented in section 3.2, section 3.3, and section 3.4 respectively. The performance evaluation is made in section 4. Section 5 concludes this paper.

2 RELATED WORKS

Jadoon et al. [7] justified the location based routing protocol shows good performance in terms of throughput, end to end delay, packet loss using various mobility patterns. Hatem Abdul-Kader et al.[8] identified the database location of the moving object cannot update continuously and considered the Modelling of the moving object database and also the author used petrinet model for location updating in object tracking. Nijad Al-Najdawi et al.[9] presents a low cost automatic object tracking algorithm and used a simplified version of the Kanade-Lucas-Tomasi technique to detect the features of both continuous and discontinuous nature. Finally the author proposed Kalmanfilter for the purpose of seeking optimal estimates in tracking.
Y.E.M. Hamoudaa et al. [10] suggested using adaptive sampling for collaborative multi-target tracking in sensor networks, where the sampling interval is computed at each

step in such a way that the prediction is succeed and the tracking is continued and it provides a significant improvement in energy efficiency while maintaining acceptable accuracy. S. Bhatti et al. [11] Found Cluster-Based Target Tracking Strategy to allow fault tolerance with a minimum energy consumption and high tracking probability and there by varying the number of nodes, cluster heads and target speed. By organizing the network into clusters, this scheme is capable of tracking the moving target as well as recovering nodes and cluster heads from failures. George K. Atia et al. [12] identified Sensor Scheduling for Energy-Efficient Target Tracking in Sensor Networks to correspond to the problem of tracking an object moving randomly through a dense network of wireless sensors and devised approximate strategies for scheduling the sensors to optimize the trade-off between tracking performance and energy consumption for a wide range of models.

Guido H.Jajamovich et al. [13] felt kalman filter to solve the multitarget tracking and sensor localization tasks when the number of targets is known and there is no uncertainty in the origin of their measurements. Zou et al. [14] used target localization based on virtual forces. It focuses on sensor deployment strategies that maximize the coverage by binary sensor detection and probabilistic sensor detection models for low and high detection accuracy. Yingqi Xu et al. [15] address the energy conservation issues in the reporting operations and it propose the Dual Prediction Reporting (DPR) mechanism, in which the sensor nodes make intelligent decisions about whether or not to send updates of objects movement states to the base station and thus save energy. The energy savings achieved by DPR are stable under the ranges of mobile object dynamics considered in this paper. Aslam et.al. [23] Opined that a filtering style tracking algorithm will detect the targets using binary sensors

Kyriakakos et al. [24] initiated a path prediction algorithm that exploits the machine learning algorithm of learning automata. The decision of the learning automaton is driver by the movement patterns of a single user but is also affected by the aggregated patterns demonstrated by all users. O.Wolfson. et al. [16] offered to revise the motion plans of moving objects using the predicted travel-speeds. This revision occurs before answering queries. The accuracy of query processing with travel-speed prediction may be improved by using a more sophisticated travel speed prediction method.

M. J. Miller et al. [17] presented a protocol in which energy is conserved by amortizing the energy cost of communication over multiple packets. In addition, author allows sensors to control the amount of buffered packets since storage space is limited. To achieve this, a two-radio architecture is used which allows a sensor to wake up a neighbor with a busy tone and send its packets for that destination. Xue et al. [18] offered solutions to minimize the energy consumptions for real time task in wireless embedded systems. D. Estrin et al. [19] described the directed diffusion for designing distributed sensing algorithms. To achieve energy savings it enables diffusion by selecting good paths and by caching and processing data in network. B. Liang et al. [20] suggested a novel predictive distance-based mobility management scheme, which takes full advantage of the correlation between a mobile's current velocity and location and its future velocity and location.

Y.Shang et al. [21] formulated the idea of converting the distance information in to the coordinate vector has become prevalent in Wireless sensor network localization and also used classical Multidimensional Scaling to find the configuration of points in space that satisfies a set of supplied dissimilarities. Wang et al. [22] offered the localization problem as a graph embedding problem and then use the kernel locality preserving projection technique to estimate the relative locations of all sensor nodes.

3. PROBLEM STATEMENT

In this section we state the problem. Given a set of m sensor nodes with known location (x_i, y_i), $1 \le i \le m$ and a set of n objects with unknown location (x_o, y_o), $1 \le o \le n$ and a set of distance estimation d_{io}, where $1 \le i, o \le m, i \ne o$, we have to determine the location of every missed object, such that the missing object can be retain to the tracking process. In solving this stated problem, some important metrics should be considered named Energy consumption and location error. In order to promote the lifetime of the whole network, energy dissipation and location error are to be minimized and this is the aimed goal of this paper.

3.1 System Description

In this work, we assume that sensor nodes are static and the topology, location of sensor is well known to base station and we also assume that the communication between the senor nodes and the base station are based on multi hop communication. We adopt a network model as proposed in [6] where a sensor node is activated only where there is an object in its monitor region. Besides, the activated node is scheduled to be in active mode for X seconds and in sleeping mode for (T - X) seconds during the T seconds periodically to save the energy as shown in Fig 1. Its ability to predicting the objects future movements and to tracking them with the less number of sensor nodes, while keeping the rest of the sensor nodes in the network in a sleep mode.

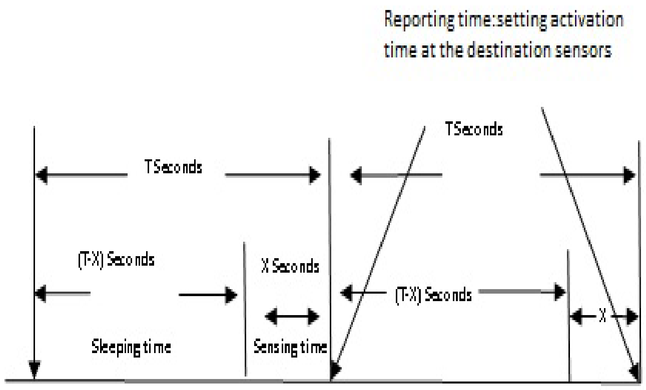

Fig 1.Relation between X, T, (T-X)

Since we are using a prediction technique to determine the future movements of a moving object, it is possible to find some missing objects during the tracking process. Therefore, there is a need to develop a solution to find any missing object and return the network to the prediction tracking process. When dealing with object tracking, there is uncertainty in the association between objects and measurements. Each sensor produces a set of unlabelled measurements and therefore the tracking algorithm has to estimate the measurements of these object produced or if the measurement is due to noise the object tracking is performed by obtaining an estimate of its state. When the number of objects to be tracked is more than one, a multi object state is considered by check each individual object state.

In this paper, based on Atomic multilatertion and collaborative location estimation, we propose an object tracking algorithm to accurately track an object using a prediction-based technique. When a sensor detects the object, it will store the object information in its local memory, but it is very likely that the detecting result is affected by noise and other environmental factors, resulting in inaccurate object location estimation. Therefore, we further estimate the position of an object using Bayesian estimation method to reduce the effect of noise. Bayesian estimation method uses all known information to construct the posterior probability density of the system state variables. It means, it predicts the priori probability density of the state according to the prediction based model of the system, and then uses the newest measurement to amend the posterior probability resulting in optimal state estimation.

3.2 Atomic Multilatertion

Position of an object in the plane is determined by two parameters namely x and y coordinates. The distance measurement with respect to the landmark, places the object in a circle centered at the landmark where radius is the measured distance.

In general the distance measurement is very essential to completely localize an object. For example, suppose we number the object whose location is mentioned as object 0 and the available landmark nodes are mentioned as 1, 2, n as shown in Fig 2. Let the position of the node i be (x_i, y_i) and its Time of Arrival at object 0 to be t_i (for $1 \le i \le m$)

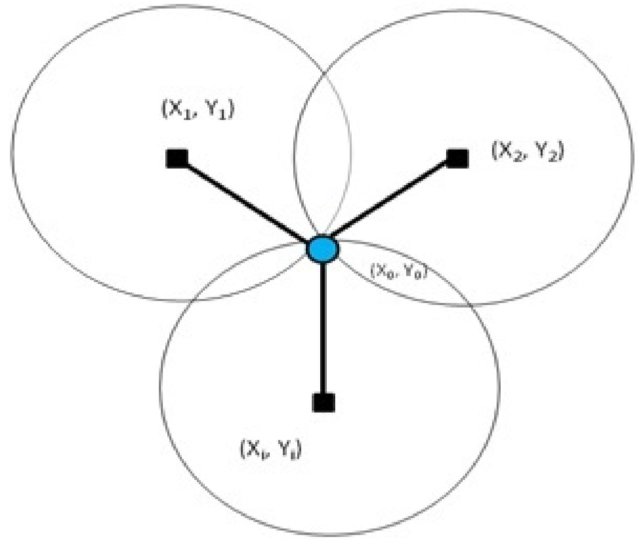

Fig 2. Location Calculations

If s denotes the local signal propagation speed, then for each i, $1 \le i \le n$

$$\sqrt{(x_i - x_0)^2 + (y_i - y_0)^2} + \varepsilon_i(x_0, y_0, s) = st_i \qquad (1)$$

where ε_i , Denotes the error, i^{th} measurement due to noise.

Our goal is to estimate(x_o, y_0) and s, to minimize the weighed total squared error

$$\varepsilon(x_0, y_0, s) = \sum_{i=1}^{n} \delta_i^2\ \varepsilon_i^2\ (x_0, y_0, s) \qquad (2)$$

Assume $\delta^i = 1$

We can linearize above system of n constraints by squaring and subtracting the equation (2) and obtaining linear equation of the form

$$2x_0(x_i - x_1) + 2y_0\,(y_i - y_1) + s^2\,(t_i^2 - t_1^2) = (x_i^2 - y_i^2) + (x_i^2 - y_1^2) \qquad (3)$$

We treat s 2 as new variable, we can write this in matrix form as V=UA

Where $U = \begin{pmatrix} x_0 \\ y_0 \\ s^2 \end{pmatrix}$

$$A = \begin{pmatrix} 2(x_2 - x_1) & 2(y_2 - y_1) & t_2^2 - t_1^2 \\ 2(x_3 - x_1) & 2(y_3 - y_1) & t_3^2 - t_1^2 \\ 2(x_n - x_1) & 2(y_n - y_1) & t_n^2 - t_1^2 \end{pmatrix} \text{ And}$$

$$V = \begin{pmatrix} -x_2^2 - y_2^2 + x_1^2 + y_1^2 \\ -x_3^2 - y_3^2 + x_1^2 + y_1^2 \\ -x_n^2 - y_n^2 + x_1^2 + y_1^2 \end{pmatrix}$$

The solution to the system is given by

$$U = (\,(A^T A)^{-1} A^T) \times V \qquad (4)$$

The Atomic multilateration scheme considers coordinates calculation in location estimation process as a parameter in estimation problem. Specifically in multilateration scheme, the imprecise distance estimation ε_i is often the main source of error.

3.3. Collaborative Location Estimation

Object Location Estimation can be calculated using Standard Estimation Theory [2].

$$z_i^t = h(x^{(t)}, \lambda_i^{(t)}) \quad (5)$$

$z_i^{(t)} \rightarrow$ Time dependent measurement of sensor
$\lambda_i^{(t)} \rightarrow$ Sensor characteristic
$x^{(t)} \rightarrow$ Parameter
Estimate nonlinear relation between sensor type, sensor position, and noise model and parameter,
Equation (5) can be written as

$$h\left(x^{(t)}, \lambda_i^{(t)}\right) = f_i(x^{(t)}, \lambda_i^{(t)}) + w_i^{(t)} \quad (6)$$

Where f_i is non linear function and w_i is noise with known covariance, if f_i is a linear function
Equation (6) can be written as

$$h(x^{(t)}, \lambda_i^{(t)}) = Hi(\lambda_i^{(t)})x^{(t)} + w_i^{(t)} \quad (7)$$

Assume static vector x =[x,y] T is the unknown object position

$$\lambda_i = [\delta_i, \sigma i2]\ T \quad (8)$$

Where, δ_i is known sensor position.
σi is additive noise variance

Assume signals transmit isotropic ally. Parameters are related to the measurement by

$$z_i = \frac{a_i}{||X-\delta_i||^{\alpha/2}} + w_i \quad (9)$$

Where a_i is random Variable
Where w_i is Gaussian variable with variance σi2
Where $\propto$ is known attenuation coefficient.

Assume α =2 in Equation- (9)
Let $x \in \mathbb{R}^2$ is the position of the object and
Let $\delta_i \varepsilon\, \mathbb{R}^2$ is the position of the sensor i and
Zi is the amplitude measurement of the sensor.

By omitting noise term signal model, equation (9) can be rewritten as

$$||x||^2 + ||\delta_i||^2 - 2x\delta_i = \frac{a_i}{z_i} \quad (10)$$

Where i= 1, 2,…….

To generate a set of linear constraint, assume i= 1 and obtain

$$-2(\delta_i - \delta_1)^T x = a_i(1/z_i - 1/z_1) - ||\delta_i||^2 - ||\delta_1||^2 \quad (11)$$

Let $c_i = -2(\delta_i - \delta_1)$ and $d_i = a_i(1/z_i - 1/z_1) - ||\delta_i||^2 - ||\delta_1||^2$

Equation (11) can be re written as

$$c_i^T x = d_i \quad (12)$$

Through given m sensors, we obtain m-1 linear constraints, Therefore equation (12) can be re written as

$$C_{m-1}x = d_{m-1} \quad (13)$$

By using least square method equation (9) can be written as

$$x = [(c_{m-1}^T\, c_{m-1})^{-1}\, c_{m-1}^T]d_{m-1} \quad (14)$$

3.4. Bayesian iterative Estimation

Goal of object location estimation is to obtain a good estimate of the object state $x^{(t)}$ from the sensor location history $z^{(\bar{t})}$.We use p (x) which denotes priori probability distribution function about statex. P(z/ x) denotes likelihood function of z given x. P(x/z) denotes posteriori distribution of x given z

Relationship p(x/z), p(x),p(z/ x) is given by Bayesian theorem

$$P(x/z) = \frac{p\left(\frac{z}{x}\right)p(x)}{\int p\left(\frac{z}{x}\right)p(x)dx} = \frac{p\left(\frac{z}{x}\right)p(x)}{p(z)} \quad (15)$$

Where p(z) is marginal distribution called normalizing constant
Bayes rule can be written as

$$P(x/z) = k.P(z/x)\ p(x) \quad (16)$$

Using this Bayes rule iterative estimation of the true state can be produced.
Moreover Mean of the distribution can be calculated using minimum mean squared error estimator

$$\bar{x} = \int x\, p\left({}^{X}/_{z_1} \ldots\ldots {}^{X}/_{z_n}\right)dx \quad (17)$$

Finally residual uncertainly of the estimate is approximated by the covariance

$$\varepsilon = \int (x - \bar{x})\,(x - \bar{x}))^T\ p\left({}^{X}/_{z_1} \ldots\ldots {}^{X}/_{z_n}\right)dx \quad (18)$$

In order to accurately locate the position of the missed object O, iterative estimation of the mean can be calculated

$$O = \frac{1}{n}\sum_{i=1}^{n}\bar{x}(i) \quad (19)$$

$$O(n) = \frac{1}{n}\sum_{i=1}^{n}\bar{x}(i)$$

$$O(n) = \frac{1}{n}\sum_{i=1}^{n-1}\bar{x}(i) + \frac{1}{n}\bar{x}(n)$$

$$O(n) = \frac{(n-1)}{n}\ X\ \frac{1}{n-1}\sum_{i=1}^{n-1}\bar{x}(i) + \frac{1}{n}\bar{x}(n)$$

$$O(n) = \frac{(n-1)}{n} \; O(n-1) + \frac{1}{n}\bar{x}(n) \quad (20)$$

We made observations in equation (16) by adding noise to the true state priori probability distribution function about state x can be calculated using normal distribution $N(\mu, \sigma^2)$.

$$p(x) = \frac{1}{\sigma\sqrt{2\pi}} e(-(x-\mu)^2/(2\sigma^2)) \quad (21)$$

Where σ is the standard deviation and μ is the mean. True State will be estimated using the posterior estimate from the previous observation as the prior for the next observation. The tracking algorithm utilizes posterior probability at every time step to estimate the location of a missed object, by using the iterative estimation of prior probability.

4 PERFORMANCE EVALUATIONS

We conduct the computer simulation to show the efficiency of the proposed methods. The tracking algorithms are coded in Mat lab. Simulations are carried out with 100 logical sensor nodes in a 100x100 m^2 monitor area. We assume the sensing coverage range to be 15m. The network is based on grid topology as shown in Fig 3. We assumed that there are a certain number of key paths that an object may follow, in addition we assume that an object may choose a random path .Sensor node sends a report regarding the location of the moving object every 500 ms to the application. Every simulation will last for 120 s. We have conducted 200 trials to get an average value of the results for energy consumption, location error. TABLE 1 describes the Simulation settings and TABLE 2 describes the Sensor node energy consumption. We carry out the simulations to measure total energy consumption and location error.

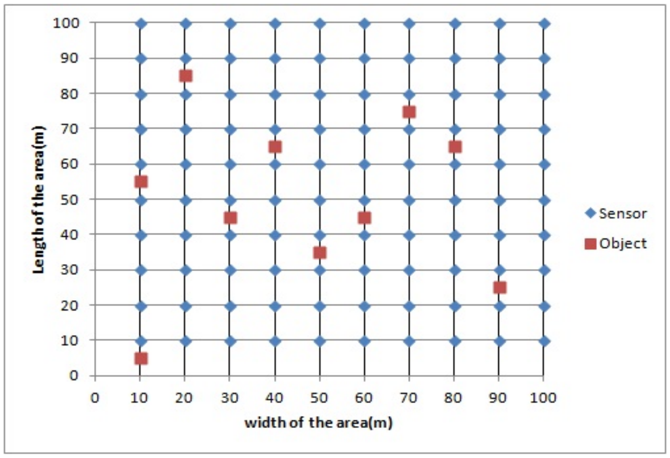

Fig 3: Distribution of sensors and Objects

TABLE 1
Simulation settings

Number of Sensors	100
Sensing Area	100x100 m2
Sensing Range	15 m
Object Speed	5 m/s

TABLE 2
Sensor Node Energy Consumption

Component	Mode	Energy consumption (mW)
MCU	Active	360
MCU	Sleep	0.9
Sensor	Active	23
Radio	Transmission	720
Radio	Receiving	369

4.1 Total Energy Consumption

Total Energy Consumption is the amount of energy consumed by the whole network to monitor the moving objects, which includes active and sleep mode during simulation. Let BE denote Bayesian estimation, CL denote collaborative location Estimation and AM denote Atomic multilateration as shown in Fig 4. The total energy consumption is greatly influenced by accuracy in prediction and when the object is moves out of the coverage area, sensor loose needless energy.

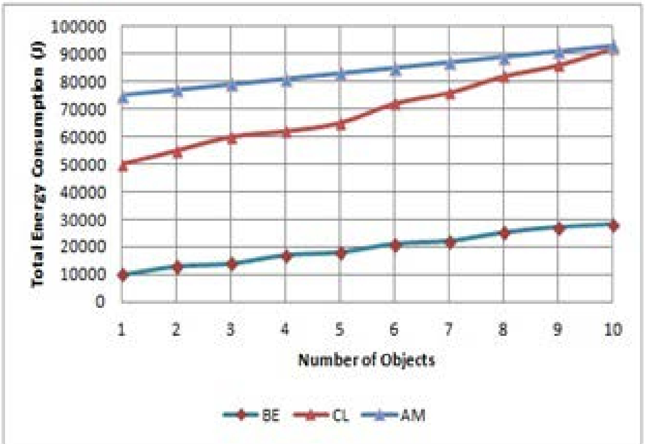

Fig 4.Simulation results of Total Energy Consumption

4.2 Location Error

Let object (R) denote the Real position of the object and object (E) denote the estimated position of the object in a sensor network as shown in Fig 5 and the location error is the distance between the estimated position and the actual position of an object. Among all the schemes, the atomic multilateration scheme performs worst, mainly because it has less information available for the next step calculation after the elimination of quadratic term. The Collaborative location estimation avoids such problems. Thus, it outperforms the atomic multilatertion methods. As shown in Fig 6, Bayesian Estimation method outperforms all the other methods. Specifically, we denote (x_i, y_i) as the correct coordinates of sensor i and (x_0, y_0) as the imprecise coordinates of an object. So location error = $\sqrt{(x_{i-}x_0)^2 + (y_{i-}y_0)^2}$.

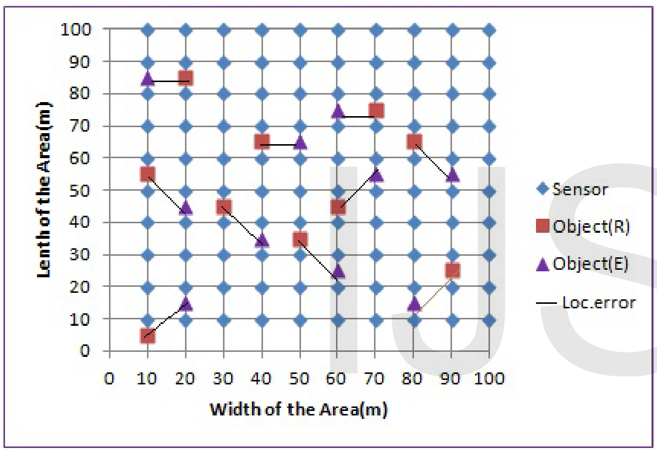

Fig 5. Real Position and Estimated Position of Objects.

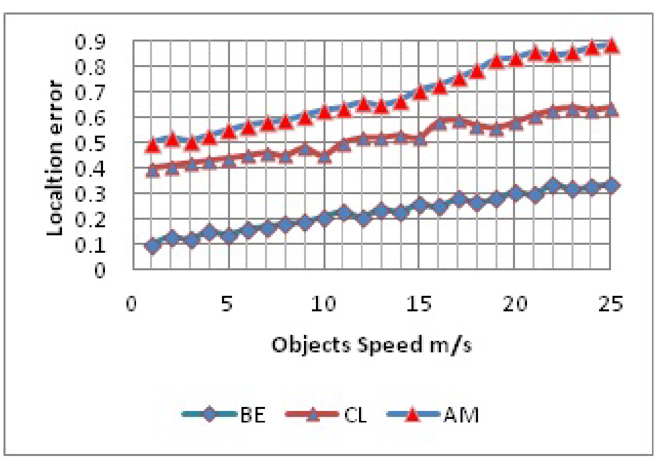

Fig 6. Simulation Results of Location Error

5 CONCLUSIONS

In this paper, we focused with the problem of coordinate calculation in location estimation process. This problem enables to find the real location and estimated location of an object, given a set of sensor nodes coordinates and its measurements. When the proposed methods are applied to computer simulation, it shows significant reductions in energy dissipation are achieved by using collaborative location estimation when compared with atomic multilateration. We come to know that proposed Iterative Bayesian estimation method performance is outstanding almost in all situations that were studied and the simulation results prove that the Bayesian estimation achieves good concert and it surpass atomic multilatertion and collaborative location estimation in terms of energy efficiency and location errors.

REFERENCES

[1] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam and E. Cayirci., “Wireless Sensor Networks: a Survey”, Computer Networks, vol.38, pp.393-422, 2002.

[2] F. Zhao and L. J. Guibas., “Wireless Sensor Networks. An Information Processing Approach”, San Mateo, CA: Morgan Kaufmann, 2002.

[3] Y. Xu and W.C. Lee., “On Localized Prediction for Power Efficient Object Tracking in Sensor Networks”, in proceedings of 1st International Workshop on Mobile Distributed Computing, pp. 434–439, 2003.

[4] D. Estrin, R. Govindan, J. Heidemann, and S. Kumar.”Nextcentury challenges: Scalable coordination in sensor networks”, in proceedings of the ACM/IEEE International Conference on Mobile Computing and Networking, pp. 263 -270, 1999.

[5] S. Goel and T. Imielinski. “Prediction-based Monitoring in Sensor Networks”: ACM SIGCOMM Computer Communication Review on wireless extensions to the internet, vol. 31(5), pp. 82 - 98, 2001.

[6] Y. Xu, J. Winter, and W.-C. Lee, “Prediction-Based Strategies for Energy Saving in Object Tracking Sensor Networks”, in proceedings of IEEE Int. Conf. Mobile Data Manage. Berkeley, CA, pp. 346–357, 2004.

[7] Misbah Jadoon, Sajjad Madani, Khizar Hayat, and Stefan Mahlknecht., "Location and Non-Location Based Ad-Hoc Routing Protocols under Various Mobility Models: A Comparative Study", Int. Arab J. of Inf. Tech., vol. 9, No.5, September 2012

[8] Hatem Abdul-Kader and Warda El-Kholy., "Modelling of Updating Moving Object Database Using Timed Petri Net Model", Int. Arab J. of Inf. Tech.,, vol.7, No.1, January 2010.

[9] Nijad Al-Najdawi, Sara Tedmori, Eran Edirisinghe and Helmut Bez., "An Automated Real-Time People Tracking System Based on KLT Features Detection", Int. Arab J. of Inf. Tech., Vol. 9, No.1, January 2012

[10] Y.E.M. Hamoudaa and C. Phillips., "Adaptive Sampling for Energy-Efficient Collaborative Multi-Target Tracking in Wireless Sensor Networks", IET Wireless. Sens. Syst., Vol.1, Issue 1, pp. 15–25, 2011.

[11] S. Bhatti J. Xu and M. Memon., "Clustering and Fault Tolerance for Target Tracking Using Wireless Sensor Networks", IET Wireless. Sens. Syst., vol. 1, Issue. 2, pp. 66–73, 2011.

[12] George K. Atia, Venugopal V. Veeravalli, Jason A. Fuemmeler., "Sensor Scheduling for Energy-Efficient Target Tracking in Sensor Networks", IEEE Transactions on Signal Processing, vol. 59, No. 10, 2011.

[13] Guido h.Jajamovich and xiadong Wang. "Joint Multitarget Tracking and Sensor Localization in Collaborative Sensor Networks", IEEE Transactions on Aerospace and Electronic systems, vol. 47, No. 4, 2011.

[14] Y. Zou and K. Chakrabarty., "Sensor Deployment and Target Localization Based on Virtual Forces," in IEEE Infocom, pp. 1293–1303, 2003.

[15] Yingqi Xu, Julian Winter, Wang-Chien Lee., "Dual Prediction-based Reporting for Object Tracking Sensor Networks", in proceedings of the first Annual International Conference on Mobile and Ubiquitous Systems: Networking and Services", pp. 154-163, 2004.

[16] B. Xu and O.Wolfson., "Time-series prediction with applications to traffic and moving objects databases", in proceedings of the ACM international workshop on Data engineering for wireless and mobile access, pp. 56–60, 2003.

[17] M. J. Miller and N. H. Vaidya. "Minimizing energy consumption in sensor networks using a wakeup radio". In Proceedings of the IEEE Wireless Communication and Networking Conference, Atlanta, GA. pp. 2335-2340, 2004.

[18] C.Xue, Z.Yuan, G.Xing, Z.Shao and E.H.M. Sha.,"Energy efficient operating mode assignment for real-time tasks in wireless embedded systems", in proceedings of the 14th IEEE International conference on Embedded and Real time computing systems and Applications, Taiwan. pp. 237-246, 2008.

[19] C. Intanagonwiwat, R. Govindan, and D. Estrin. "Directed diffusion: a scalable and robust communication paradigm for sensor networks", in proceedings of the International Conference on Mobile Computing and Networking, Boston, Massachusetts, pp. 56–67, 2000.

[20] B. Liang and Z. J. Haas. "Predictive distance-based mobility management for PCS networks", in proceedings of the 22nd Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM), pp. 1377–1384, 1999.

[21] Y.Shang, W.Rumi, y.Zhang, M.Fromherz., "Localization from mere connectivity", in proceedings of the Fourth ACM International symposium on Mobile AdHoc Networking and Computing, pp.201-212, 2003.

[22] C.Wang, J.Chen, Y.Sun, X.shen. "A graph embedding method for wireless sensor networks localization", in Proceedings of Global Telecommunications Conference, (GLOBECOM 2009), pp. 1-6, 2009.

[23] JavedAslam, ZackButler, Florin Constantin, Valentino Crespi, George Cybenko, Daniela Rus.,"Tracking a moving object with a binary sensor network", in proceedings of the First ACM conference on Embedded Networked sensor systems, pp. 150-161, 2003.

[24] Kyriakakos, M., Hadjiefthymiades, S., Frangiadakis, N., Merakos, L.F., 2003. "Multi-user driven path prediction algorithm for mobile computing", in Proceedings of 14th International Workshop on Database and Expert Systems Applications (DEXA'03), pp. 191–195, 2003.