Asian Journal of Information Technology 15 (2): 191-198, 2016
ISSN: 1682-3915

Prediction Based Location Estimation in Wireless Sensor Network

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Abstract: As, it is one of the applications of Wireless Sensor Network (WSN), object tracking is a challenging task in identifying the object in its detection area as well as informing its recent location in advance. Mostly, prediction scheme is applied in object tracking to maintain the low missing rate. When the objects are found missing, they have to be localized. Hence, more focus is given in enabling the missing object recovery by using the proposed optimization algorithm such as Simulated Annealing (SA) with Fuzzy Inference System (FIS) in a WSN and the extensive simulations are also shown to demonstrate the effectiveness of the proposed algorithm against the localization methods like centroid and multilateration to estimate its performance in terms of localization error.

Key words: Wireless sensor network, localization, fuzzy inference system, simulated annealing, centroid, multilateration

INTRODUCTION

A WSN is built with number of sensor nodes functioning together to monitor a region to obtain data about the surroundings. These sensor nodes are low power devices equipped with a sensing unit, a processing unit, a communication unit and a power unit (Yick *et al*., 2008). Since, sensor nodes have inadequate memory and are typically deployed in complex locations, a radio is put in to service for wireless communication to transfer the data to the sink.

Depending on the applications and the type of sensors used, actuators may be integrated in the sensors. In WSN, many sensor nodes need to keep on working altogether with neighboring nodes in order to track the moving objects. However, in some of the sensor network, nodes are grouped in to different clusters and each cluster will have a collection of Member Nodes (MN) with a Sensing Leader (SL) (Jin *et al*., 2006). The SL will communicate with rest of the MNs in the clusters and the clusters will communicate with other clusters via the SL to track the moving object, as shown in the Fig. 1.

Clusters are the organizational unit for WSNs. The opaque nature of these networks should be broken down into clusters to simplify tasks. MN is a sensor node which is the core component of a Cluster. MN can take on multiple roles in a network such as sensing, routing, data storage and data processing. SL is the organization leader of a cluster. It is often required to manage activities in the cluster which include the data-aggregation and organizing the communication schedule of a cluster. Sink is located at the outside of the cluster in a WSN. It provides

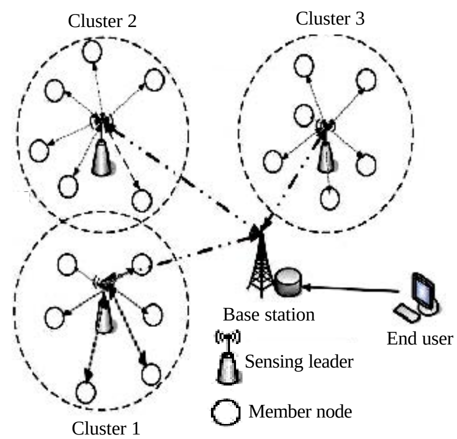

Fig. 1: Wireless sensor

is located at the outside of the cluster in a WSN. It provides communication link between the cluster and the end-user. The data in a sensor network can be used for a wide-range of applications (Yick *et al*., 2008). Therefore, a particular application may make use of the network data over the internet by using a computer.

Object tracking is one of the challenging sensor network applications which is used in intrusion prevention, wild life detecting, robotics, pervasive surveillance, manufacturing, military, building monitoring and air traffic control (Yan *et al*., 2008). The main duty of an object tracking is to track a mobile object and to report its most recent location in the detection area to the application in a well-timed manner. Here, the MNS sample the physical world for a sampling duration to obtain the properties of the object. During sampling, the MCU and

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the sensor components are activated for data collecting and processing. The MN which detects the object in their detection area has to report to the sink with certain reporting frequency.

Object tracking in WSN can be classified in to five types such as naive, scheduled monitoring, continuous monitoring, prediction-based scheme and dynamic clustering. Among them, the continuous monitoring, dynamic clustering and prediction-based scheme are specially, considered for resolving the object tracking problem (Wang *et al*., 2008; Zou and Chakrabarty, 2003; Savvides *et al*., 2001).

Prediction based object

Tracking: Here, the prediction based scheme is used to minimize the MNs participating in tracking process and make the rest of MNs in to sleeping mode (Yick *et al*., 2005). Prediction based scheme consists of prediction model, wakeup process and recovery process. Based on different prediction models, prediction can be classified as circle based, kinematics based and probability based. Circle based model is the simple and most commonly used prediction model based on the maximum velocity of the object. Kinematic based model is used, when object movement is restricted. The probability model is used when object, whose motion patterns follow some given distributions.

At last, the Prediction models use Wake-up Mechanism to wake up the neighboring MNs before the object leaves its own detection area and enters the neighboring area (Wang *et al*., 2008). There still will be un-ignorable increase of missing rate when the object change its moving direction away from the prediction because only the MNs which are on the predicted route of the mobile object would wake up and monitor the object regularly and also all the MNs on the object's traveling route are supposed to be active to monitor the mobile object. In such cases, the energy consumption would be high (Gao *et al*., 2005; Yan *et al*., 2008; Balasubramanian *et al*., 2004). If the object missing rate occurs then, the recovery process has to be initiated to localize the missing object and revisit to the network for object tracking. However, existing researchers concentrate on source, destination and neighbor recovery by activating all sleeping MNs to find out the missing object. If this case fails, which shows the way to flooding recovery (i.e.) wakes up all the MNs in the network and put the network in high energy consumption (Naderan *et al*., 2009; Xu *et al*., 2004; Xu and Lee, 2003). In order to overcome this situation an optimization algorithm such as simulated annealing with Fuzzy Inference System (SA, FIS) is proposed to localize the missing object, when the object is not found by the Mns during object tracking. In order to be different from other researches, the aim of this study is to minimize the localization error by using the proposed algorithm and to extend the lifetime of the network.

Table 1: Energy consumption in member node

Component	Mode	Energy consumption (mw)
MCU	Active	360.0
MCU	Sleep	0.9
Sensor	Active	23.0
Radio	Transmission	720.0
Radio	Reception	369.0

In this study, it is assumed that the MNs are immobile and objects are mobile and that the network topology is well-known to sink and also the multi hop communication is used between MNs and the Sink for communication. It is also assumed that the low energy paging channel exists for a MN to wake up nearby MN while in sleep mode (Xu *et al*., 2004). Here, the shortest path multi-hop routing algorithm is used for communication between the Sink and MNS. The energy consumption in a MN is given in Table 1.

MATERIALS AND METHODS

Localization methods

Centroid method: In this method, a set of MNs with known location $(x_1, y_1), (x_2, y_2)\ldots(x_n, y_n)$ and each object predictable location is computed as a centroid of the position of all connected Mns to itself by:

$$X_p, Y_p = \frac{x_1 + \ldots x_n}{N}, \frac{y_1 + \ldots y_n}{N} \quad (1)$$

Where:

(x_p, y_p) = Represents the predictable position of the object
N = The number of connected MNs to the object

Multilateration method: It is assumed that a set of MNs are placed with known location $(x_1, y_1), (x_2, y_2), (x_n, y_n)$ and an object is with unknown location (x_p, y_p) distributed in a cluster, as shown in Fig. 2. The distance between different MN and the object is respectively $d_1, d_2, \ldots d_n$. So, that the location of the missing object can be calculated by solving non linear system of equation:

$$\begin{cases} (x_1 - x)^2 + (y_1 - y)^2 = d^2{}_1 \\ (x_n - x)^2 + (y_1 - y)^2 = d^2{}_n \end{cases} \quad (2)$$

The system can be linearized (Savvides *et al*., 2001) by subtracting the last equation from the first n-1 (Eq. 3):

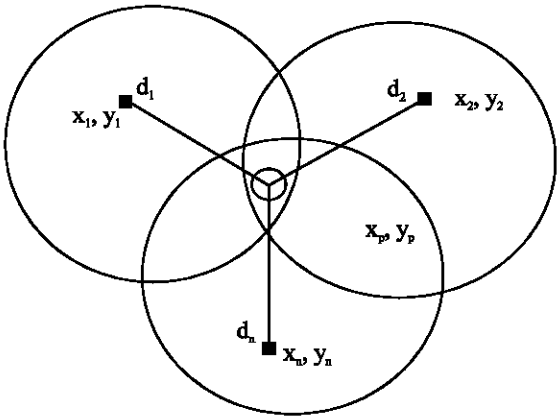

Fig. 2: Multilatertion

$$\begin{cases} x_1^2 - x_n^2 - 2(x_1 - x_n)x_p + y_1^2 - y_n^2 - \\ (y_1 - y_n)y_p = d_1^2 - d_n^2 \\ x_{n-1}^2 - x_n^2 - 2(x_{n-1} - x_n)x_p + y_{n-1}^2 - y_n^2 - \\ 2(y_{n-1} - y_n)y_p = d_{n-1}^2 - d_n^2 \end{cases} \tag{3}$$

Reorder the terms gives a proper system of linear equations such as AX = B, where:

$$A = 2\begin{bmatrix} x_1 - x_n & y_1 - y_n \\ x_{n-1} - x_n & y_{n-1} - y_n \end{bmatrix}$$
$$B = \begin{bmatrix} x_1^2 - x_n + y_1^2 - y_n^2 + d_1^2 - d_n^2 \\ x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2 + d_{n-1}^2 - d_n^2 \end{bmatrix} \tag{4}$$
$$X = \begin{bmatrix} x_p \\ y_p \end{bmatrix}$$

Fuzzy inference system: Fuzzy Inference System (FIS) is the process of formulating the mapping from a given input to an output by using fuzzy logic. The mapping then provides a basis from which decisions can be made or patterns be discerned. The process of fuzzy inference involves fuzzy logic operators, if-then rules and membership functions. There are two types of fuzzy inference systems that can be executed in the fuzzy logic. They are Mamdani-type and Sugeno-type. Fuzzy inference systems have been successfully applied to data classification, automatic control, expert systems and decision analysis (Wang, 1999). Due to their multidisciplinary nature, fuzzy inference systems are related with number of names such as fuzzy-rule-based systems, fuzzy modeling, fuzzy expert systems and fuzzy logic controller's fuzzy memory.

Mamdani's fuzzy inference method is most commonly used fuzzy methodology and it is among the first control systems built by using fuzzy set theory. Mamdani fuzzy inference expects the output membership functions to be fuzzy sets. After the aggregation process is over, there is a fuzzy set available for each output variable that needs defuzzification. It is possible to use a single spike as the output membership function rather than a distributed fuzzy set, as shown in Fig. 3. This is occasionally known as a singleton output membership function and it can be considered as a pre-defuzzified fuzzy set. It improves the efficiency of the defuzzification process because, it greatly simplifies the computation and finds the centroid of a two-dimensional function.

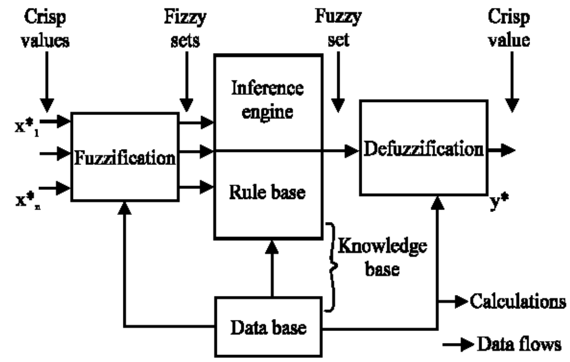

Fig. 3: Block diagram of fuzzy inference system

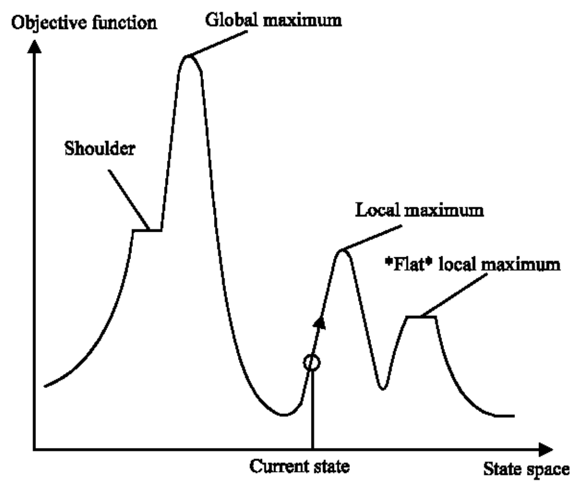

Fig. 4: Block diagram of simulated annealing

Simulated annealing: Simulated Annealing (SA) is considered as a generic probabilistic Meta heuristic for global optimization problem of locating a good estimate to the global optimum for a given function in a large search space as shown in Fig. 4. It is frequently used when the search space is discrete (Kirkpatrick *et al.*, 1983). For certain problems, simulated annealing may be more efficient than exhaustive enumeration, provided that the goal is merely to find a good solution that is acceptable in fixing the amount of time, rather than the best possible solution.

This method is an adaptation of the Monte Carlo method to generate sample states of a thermodynamic system. The name and inspiration come from annealing in metallurgy, a technique involving heating and controlled cooling of a material to increase the size of its crystals and reduce their defects.

Localization by fuzzy modelling with simulated annealing

Fuzzy modelling: The FIS used here is Mamdani fuzzy model to localize the missing object in prediction based environment. In Mamdani application, the main responsibility of the member nodes is to send out signals to identify the missing object location, by means of calculating edge weight of each member node. By using the edge weights of all member nodes, the position of the object can be determined. When the positions of the member nodes are (x_1, y_1), $(x_2, y_2)\dots(x_n, y_n)$ and the predictable position of the object is calculated by using:

$$X_p, Y_p = \frac{w_1x_1 + \dots w_nx_n}{\sum_{i=1}^{n} w_i}, \frac{w_1y_1 + \dots w_ny_n}{\sum_{i=1}^{n} w_i} \qquad (5)$$

where, n is the number of adjacent Mns. The signal strength can provide an idea about the distance from the MN to the object. The fuzzy inference system used is to model the relationship between the node weight and its signal strength. This enables the fuzzy IF-THEN rule to be in the following form:

$$R^l : \text{IF } x \text{ is } C^l \text{ THEN } y \text{ is } D^l \qquad (6)$$

Where:

R^l = Denotes the lth fuzzy rule corresponding the numerical order l of signal partition regions

x = The input value

y = The edge weight of the fuzzy rule R^l

Here, the input variable x is the signal from a MN and the output variable y is the edge weight of each MN for a given object. Input space of the signal is divided in to five membership function: very high, high, medium, low, very low and also output space of the weight is divided into five membership function: very high, high, medium, low, very low as shown in Fig. 5.

Now, consider the rules of fuzzy inference system, if an MN emits high powered signal then, the object is likely to be closer to the given node and it will have a higher weight. On the contrary, if an MN emits low powered signal then, the object will be far away from the given MN

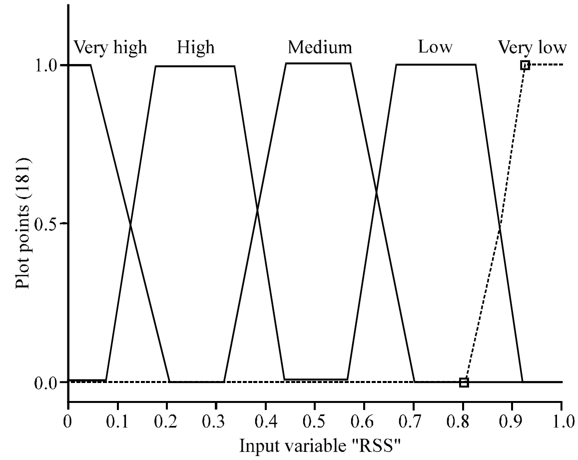

Fig. 5: Fuzzy membership functions with FIS variables

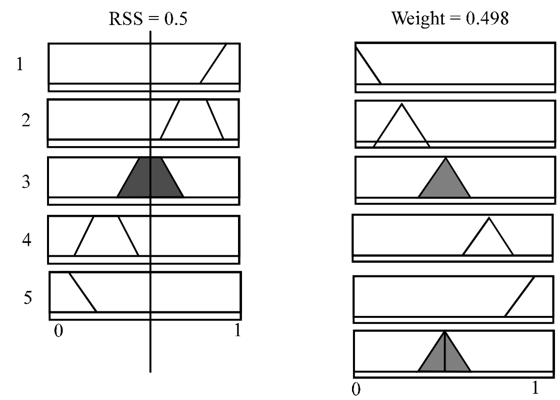

Fig. 6: Optimized fuzzy membership function using simulated annealing

and it will have lower weight. Subsequently, fuzzy rule is used to tune the membership functions. The fuzzy membership function is developed based on signal information between the MN and the object. From Eq. 6, the predicted output of the fuzzy model ($\bar{y}$) is computed as the weighted average of y and is defined as follows:

$$\bar{y} = \frac{\sum_{l=1}^{k} yw^l}{\sum_{l=1}^{k} w^l} = \frac{\sum_{l=1}^{k} D^l w^l}{\sum_{l=1}^{k} w^l} \qquad (7)$$

where, l =1, 2, 3 …..k and k denote the number of rules.

Simulated annealing optimization: For optimizing the FIS, derivative free optimization method such as Simulated Annealing (SA) is used and its aim is to get the optimal object location and reduce the localization error, as shown in Fig. 6. The pseudo code of SA is shown in algorithm A. In each iteration (k), a new location (y') is generated from

Table 2: Simulated annealing parameters

Evaluations	300000
Mutation rate	0.75
Mutation intensity	10
T	Auto
Markov chain length	30

the current location (y) and it either replaces it or does not depend on acceptance criteria. The acceptance criteria works as follows both old location (y) and new location (y’) have an associated value which are determined by a cost function C (y). If the cost function is C(y)>C(y’) then, the new location is better than the current location or else the current location is better than the new location, if C (y)<C (y’) then, it will replace with probability P. This probability P depends on a control parameter T and it is expressed as:

$$P = \frac{1}{e\left[\left(c(y)-c(y')\right)\right]/T} \tag{8}$$

For optimizing purpose, standard parameter values were used for SA as shown in Table 2. Finally, iteration count (k) is incremented. If it reaches maximum, then the iteration is stopped and then the control parameter T has to be reduced, according to annealing schedule (i.e.,) T (n+1) = ∝.T (n) where the value of ∝ is 0.25.

Algorithm A: SA

Initialize T←0
Initialize current location (y)
Set iteration count k = 1
Evaluate new location (y’)
If C(y)>C(y’) then, y =y’
Else p = exp[(C(y)-C(y’)]/T
T(n+1) = ∝.T(n),
Stop iteration

RESULTS AND DISCUSSION

Performance evaluation: To evaluate the proposed method with the existing localization methods in a spacious manner, different settings have been implemented by using ns 2 simulator. The simulation is carried out in a 100×100 m^2 detection area. It is assumed that each MN will have a coverage range of 10m with in a cluster. Table 3, for a synopsis of simulation settings. Different graphs depict performance under variations of preceding parameters. To evaluate the proposed scheme, localization error is used as the performance metrics.

Localization error: The difference between the predictable position and actual position of the object is termed as localization error and the average localization error is calculated by estimating the average difference between the predictable position and the actual position of all object s. Let (x_p, y_p) be the predictable coordinate and (x_a, y_a) be the actual coordinate of the object. Here, the proposed localization algorithm is simulated for estimating the possible locations of the missing object with the help of MN and SL. These Mns estimate their locations by using the location information of their neighboring Mns. The transmission range of all Mns is assumed to be 10 m. MNS can communicate with adjacent nodes, if its distance from the object is smaller than the transmission range as shown in Fig. 7. Also for simulation, Received Signal Strength (RSS) model is used which also takes into account of noise.

Table 3: Simulation settings

Parameters	Values
Number of sensors	100
Detection region	100×100 m^2
Sensor range	10 m
Object speed	5 ms^{-1}
Number of objects	10

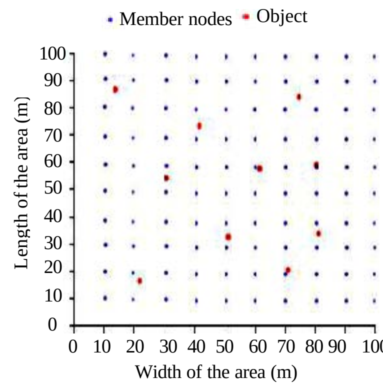

Fig. 7: Member nodes and object deployment

The proposed location estimation method (SA, FIS) is simulated and it compares its results with centroid and multilateration and the results of the localization error graph for each missing object is shown in Fig. 8-10, respectively. It can be observed from Table 4, that the average localization error for SA with FIS, multilateration and centroid are 0.97, 2.29 and 3.48 (m), respectively. From Fig. 11, it is evident that SA with FIS maintains an acceptable localization error when compared to centroid and multilateration. This is due to the proposed localization algorithm such as simulated annealing which is a kind of distributed algorithm used to estimate each missing object and predictable position independently.

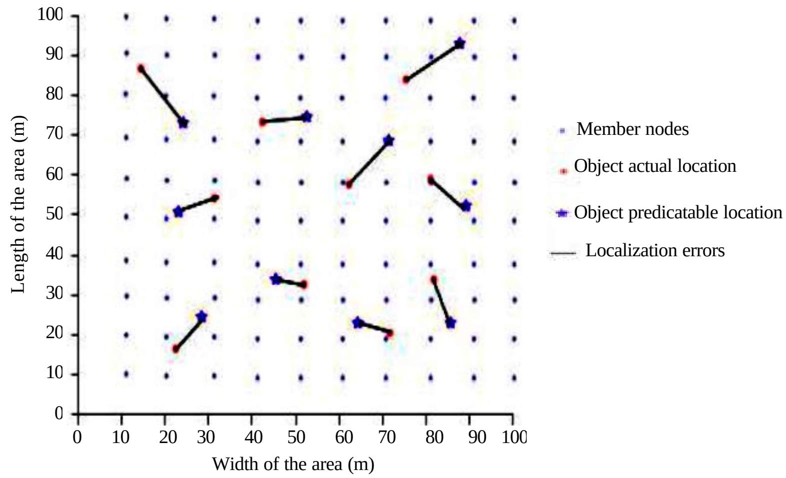

Fig. 8: Object recovery using centroid

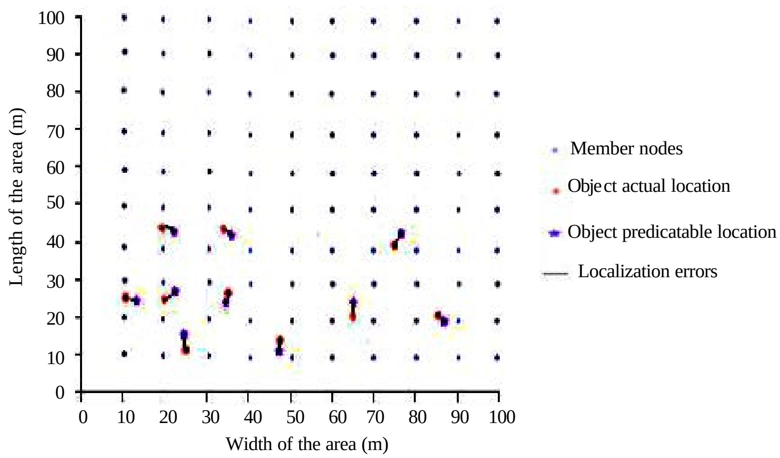

Fig. 9: Object recovery using multilateration

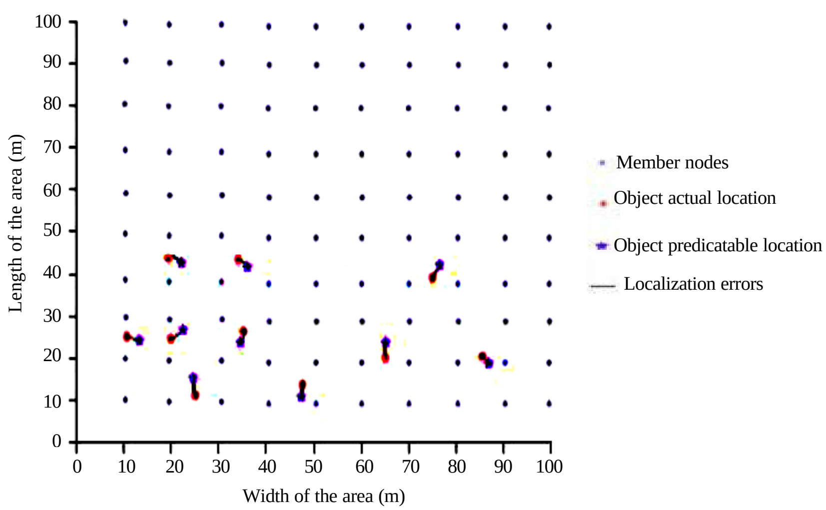

Fig. 10: Object recovery using SA with FIS

Table 4: Localization error comparison

	Localization error (m)		
Methods	Minimum	Maximum	Average
Centroid	2.54	4.10	3.48
Multilatertion	1.33	3.01	2.29
SA, FIS	0.65	1.32	0.97

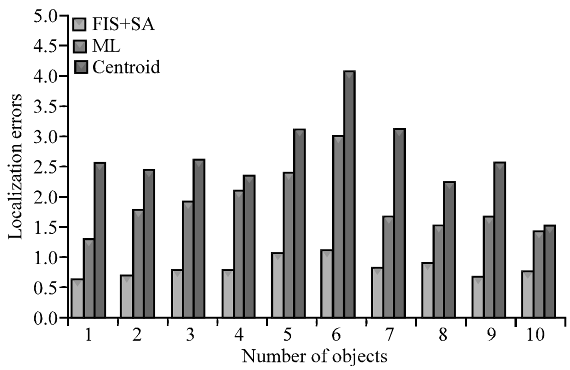

Fig. 11: Localization error analysis

CONCLUSION

In this research study, the missing object recovery problem is presented and described. This problem is related to identifying the predicted location of a missing object, given in a set of member node coordinates. Here, fuzzy inference system with simulated annealing algorithm is proposed to estimate the location of the missing object by means of frequent updating of predictable location. Furthermore, the proposed algorithm is simulated along with multilatertion and centroid methods. It has been proved that SA with FIS outperforms other methods by maintaining minimized localization error.

RECOMMENDATIONS

In future, it is planned to find out the missing object in the mobility member node environment and also implement multidimensional optimization algorithm to minimize the localization error.

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