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Efficient Localization in Wireless Sensor Networks by SFLA-BFO

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ABSTRACT

Proposed work is based on the automatic localization of sensor node in wireless sensor networks. Automatic detection of node location is a motive to make the system efficient so that they can understand the network environment by themselves and detect them. After analysis of previous work we noted that optimization algorithms are best for automatic localization of sensor nodes which performs well for unsupervised learning algorithms. A hybrid algorithm (SFLA-BFO) which is a combination of Shuffle leap frog algorithm (SFLA) and bacterial foraging optimization (BFO) algorithm were implemented. Simulation results show that the proposed method outperforms well with SFLA algorithm.

Keywords - Localization, Anchor nodes, SFLA, BFO, Estimation Error.

I. INTRODUCTION

A Wireless Sensor Network (WSN) is a decentralized wireless network composed of nodes that set up a network autonomously. To transmit data, no external network infrastructure is necessary; there is no central administration. Usually, the WSN is a distributed framework composed of small-size, embedded devices grouped into densely deployed network nodes across a significant range. The lack of components of the fixed network infrastructure enables unique techniques to be built and allows network dynamics. Restricted energy capacity, throughput, computing power and memory, poor communication efficiency, dynamically evolving network topology, are the most critical aspects to be considered. The primary contribution is to point out the Issues related to the precise localization of network nodes. The aim of localization is to fix geographical coordinates in the deployment area for each node with an unknown location. Most WSN applications include the connection of sensor readings with physical locations, e.g., control, target tracking, search, etc. In addition, even if the available knowledge of node locations is only approximate, there are great opportunities for the use of different network services, location-based routing, aggregation of data, etc. In [1] particle filtering algorithm was proposed for localization of nodes in mobile ad-hoc Networks.[3] The object tracking location estimate is used to define the direction and position of the object's movement. Research in[4] narrows the potential region by choosing three anchors between all sensing nodes in which a specific node may be located. The center of gravity of the intersection of triangles will decide the position of an object. For large-scale WSNs, the proposed modeling of location estimation for object tracking, developed using centroid-based range-free positioning technology [5] and centralized data processing technology to minimize data processing and traffic loads, is suitable. Research in [6] has set a threshold for the data volume of detected object data in WSNs. If an agent node's observed data volume is less than the threshold, the agent node sends the data directly to the sink. If the data volume collected is greater than the threshold, all collected data will be aggregated by the agent node and then sent to the sink. Each node maintains a counter denoting the minimum number of hops with each anchor, and updates the counter based on messages received.[7] DV-HOP uses a distance vector routing technique. In robotics localization, the Monte Carlo Localization (MCL)[8] methodology was adopted for use in mobile sensor network applications. MCL is a particle filter that blends robot vision and motion with probabilistic models.[9] The particle filter method is used to triangulate the location of the mobile node based on obtained signal strengths in wireless cellular networks from many known location base stations.

II. METHODOLOGY

This system is based on the automated localization of unmonitored nodes using learning nodes. This means that signal strength training with previously established regions is not given. The algorithm extracts the direct style test pattern of the desired region. Second, the shuffled frog leaping algorithm is modified, which is further improved with optimization of bacterial foraging.

A.SFLA

In SFLA(Shuffled Frog Leaping Algorithm) is based on Metaheuristic memetics.This include two stages

- Global inquest
- Local inquest

Global inquest:

Step 1: Initialization

Step 2: Generation of the virtual population

Step 3: Prioritizing and sorting frogs

Step 4: Split frogs into memeplexes

Step 5: Evolution of memetics in each memeplex

Step 6: Combine memeplexes

Step 7: Convergence analysis

Local inquest:

Each memeplex evolution is conducted independently of N times. The algorithm returns to the global quest for completion of the combination after the memeplexes have evolved.

The initial population A comprises F frogs divided into m memplexes, with p frogs (i.e. F=m*p) forming each memplex.

$$A = \begin{bmatrix} a_{11} & \ldots\ldots & a_1m \\ .. & .. & .. \\ .. & .. & .. \\ ap_1 & .. & apm \end{bmatrix} \quad \ldots..(1)$$

The original population is generated randomly, as m and p is related with anchor and non-anchor nodes, thus a population matrix is generated.

Sorting and distribution: The fitness function uses the memplexes to be evaluated. Then, in descending order, they're ranked. Best and worst memplexes are respectively called R_b and R_w.

Memplexes evolution: We use the worst approach to maximize (2). It is an endeavor to make the worst solution better than the best solution.

$B = rand(1, p)\, R_b - R_w \ldots (2)$

Where, $rand(1, p)$, is a random vector which elements are between 0 and 1.

The improvement in the worst solution is given in (1). If this is better than the previous solution, it will be memorized. For a predefined number of times, Else (1) is repeated.

$$I\, R_w = R_w + B \ldots (3)$$

If the worst solution is not improved by these equations, a new solution is created randomly.

Shuffling: Memplexes are sorted in descending order again after the worst solution has been changed. Step 3 is then repeated. The shuffling stage is repeated until a terminal state is reached..

Final condition: The algorithm stops if a predefined solution is reached.

B. CROSS OVER SFLA WITH BFO

The process of SFLA has been changed via BFO tuned technique in this work. Full Algorithm for BFO Rather than choosing the randomness of bacteria movement in BFO for the worst frog location change, it is not used here. The above equation changes the position of the worst frog by applying the difference between the worst and the best frog positions. The location of this update is now handled by the BFO property.

$I\ R_w = R_w + 0.05 \times \alpha$ … (4)

The α here is the path of the bacteria in BFO. The randomness in the direction of BFO is mixed here. Modified with SFLA frog location alerts. In addition, the modified location by equation is also verified to be less than 0.5 or not to hold the worst memplex at either 0 or1.

III. SIMULATION RESULTS

A. NETWORK SETUP PARAMETERS

NS2 is used to simulate the proposed Shuffled Frog Leaping Algorithm SFLA-Bacterial Foraging Algorithm (SFLA-BFA) protocol. We use the IEEE 802.11 for wireless Sensor Networks as the MAC layer protocol. It has the functionality to notify the network layer about link breakage. In the simulation, the number of nodes is varied as 50,100,150 and 200. The area size is 500 meter x 500 meter square region for 25 seconds simulation time. The simulated traffic is Constant Bit Rate (CBR).

TABLE 3.1. Network Simulation Parameters

Channel Type	Wireless
Network Propagation Model	Two Ray Ground
MAC Protocol	802.11
Interface Queue Type	Queue/Drop Tail/PriQueue
Link Layer Type	LL
Radio Link Control	RLC
Antenna Model	Omni
Topology	Flat Grid 500 x 500
Routing Protocol	AODV
Transmit Ratio	250Kb
Packet Size	512 bytes
Number of nodes	250
Simulation time	25 S
Node Type	RSSI
Localization Method	SFLA/BFO

B. PERFORMANCE EVALUATION METRICS

Estimation Error: For any localization algorithm, the primary performance metric is the estimation error, showing how near the estimated position is to the real location. The estimation error is measured as the difference between the estimated value and the real location.

C. SIMULATION OUTPUT

In initial states the sensor nodes are placed randomly with few anchor nodes. Anchor nodes are the nodes that are aware of their position estimates, and the non-anchor begins to discover their location based on signals obtained from their anchor nodes using SFLA-BFO technique. The simulation results were compared with SFLA.

D. SIMULATION REULTS AND ANALYSIS

Based on Nodes

The number of Nodes varied in the first experiment setup as 25, 50, 75, 100, 125, 150, 175 and 200

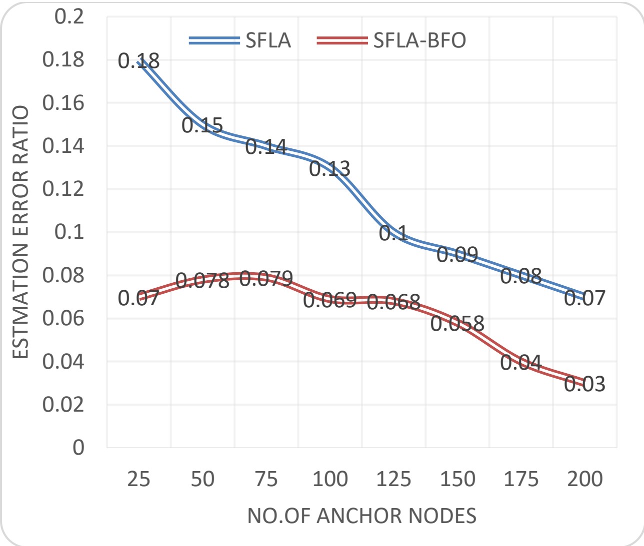

Figure 3.1 Estimation Error with respect to Anchor Nodes

The Figure 3.1 shows the effect of the anchor ratio on the estmation error. Comparing to the SFLA,SFLA-BFO gives better estimates for RSSI type nodes.

Based on Range

In second experiment, transmission range was varied as 250,300,350, 400,450 and 500m/s.

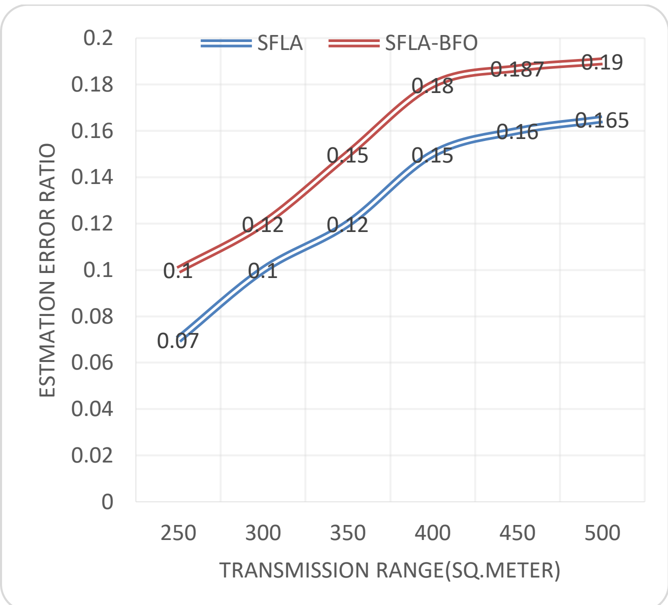

Figure 3.2 Estimation Error with respect to Transmission Range

When comparing the performance of the two algorithms, we infer that SFLA-BFO outperforms based on transmission range. The effect of coverage on estimation error shows estimation error becomes high when the network is sparse, that is of increase in transmission range.

Based on Time:

In Third experiment, Time is varied with fixed speed of mobile nodes.

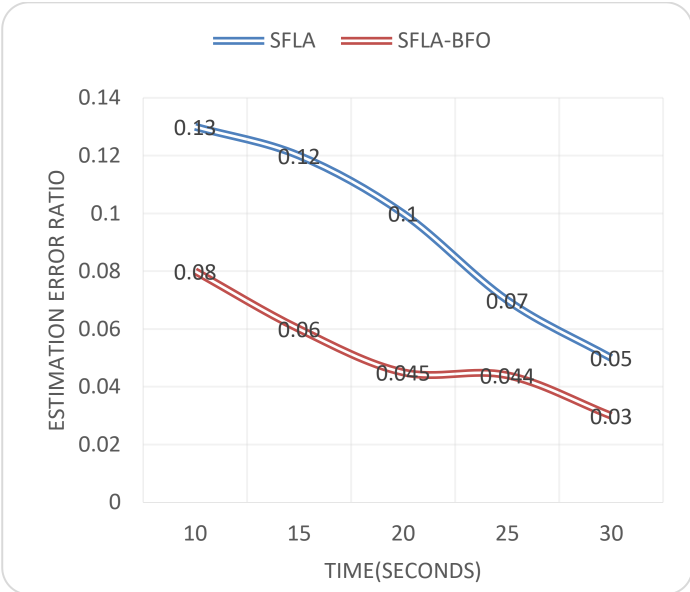

Figure 3.3 Estimation Error with respect to Time

For the fixed speed of the mobile nodes, in Figure3.3 the estimation error drops within several seconds due to increase of anchors for every time unit.

Based on Speed:

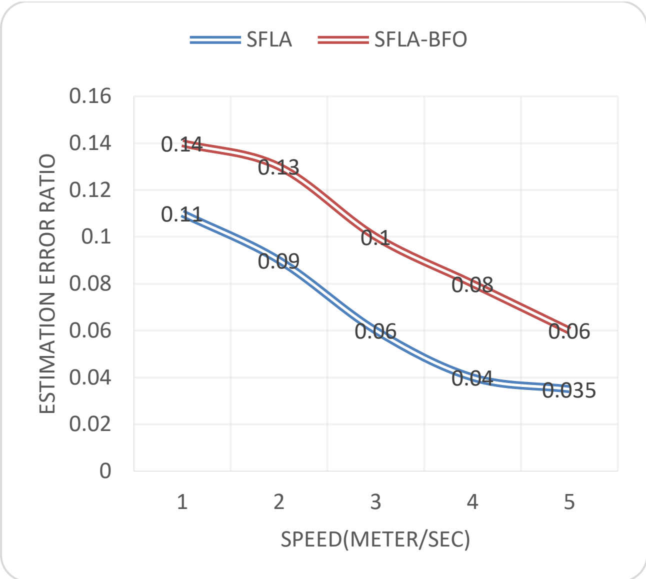

Figure 3.4 Estimation Error with respect to Speed

For varying the speed of the mobile nodes, Figure.3.4 ,the estimation error drops by quickly adapting the location changes.

IV. CONCLUSION

The proposed work is focused on the automated location identification of sensor nodes within the range of transmission. two strategies were combined, i.e. SFLA and BFO, where SFLA is the backbone in which the location of the worst frog is modified by BFO's randomness property. The suggested fitness function helps to discover the appropriate location of the nodes in the wireless sensor networks easily. The new paradigm has shown its adaptability to rapidly converge and to give accurate results. Results in terms of accuracy, precision and specificity have been compared with a single SFLA algorithm.

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