IFERP
connecting engineers... developing research

ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 5, Issue 1, January 2018

Cat Swarm Optimization based Localization Algorithm for Wireless Sensor Networks

[1] Nitin Jain, [2] Sushila Madan, [3] Sanjay Kumar Malik
[1] Assistant Professor, Department of Computer Science & Engineering, Hindu College of Engineering, Sonepat
[2] Associate Professor, Department of Computer Science, LSR College for Women, University of Delhi, Delhi
[3] Associate Professor, Department of Computer Science & Engineering, SRM University, Delhi-NCR Campus, Sonepat

Abstract: - **In Present time, Wireless sensor networks (WSNs) can be applied in many different applications areas. It is a network of sensor nodes whose primary work is to collect the data from sensing field and process these data. Hence, in WSNs, localization problem can be occurred due to lack of information about the accurate positions of sensor nodes. The localization algorithms divide into range free and range based algorithms. Due to hardware limitations of WSNs devices, range free localization algorithms are more widely adopted to determine the position of nodes in sensor fields. But, these algorithms have tendency of error during the computation of nodes positions. DV-hop is one of the popular range free localization algorithm that can widely adopted in WSNs and works on the concept of hop distance estimation. In this paper, an improved version of DV-hop localization algorithm is proposed based on cat swarm optimization algorithm, called CSO DV-Hop algorithm. The main concern of the integration of CSO algorithm with DV-Hop algorithm is to reduce the localization error of DV-Hop algorithm. The simulation results reveal that proposed algorithm enhances the location accuracy in comparison to other algorithms being compared.**

I. INTRODUCTION

In last few years, a lot of attention and research work have been carried out for successful deployment of sensors in distributed management, information processing, and multi-hop communication [1].Wireless sensor networks are integrated with advanced technology like sensor technology, embedded computing, communications, and distributed information processing. Large amount of data is gathered through deployed sensors and these sensors are also monitored environmental parameters information collaboratively [2]. Hence, energy consumption and Therefore, collaborative information processing can be considered as key issues in WSNs. But, the collaborative data processing takes less attention among research community. The WSNsare designed using large number of sensor nodes, that can deployed in a sensor field and each node responsible for multi-hop communication [3]. The primary responsibility of these sensor nodes is to collect the data from the sensor field and process the collected data weather belongs to mechanical, thermal, biological, chemical, and optical readings [4]. However, sensors have limited source of power in terms of battery and the power can be consumed due to collection and processing of data. Hence, balanced energy consumption is one of main issue for energy-efficient management [5]. In recent times, lot of research is ongoing for monitoring of residual energy in the field of WSNs. Large numbers of cluster-based routing protocols have been designed for address the above mentioned issue of WSNs. Further, it is observed these nodes are randomly deployed in the sensor field. In most of WSNs applications, it is important that the location of nodes should be known in advance for obtaining sensing data such as target tracking [5], medical care [6] and smart house application [7]. In such application, each node having information about the location of other nodes, without knowing the location information, the collected data have not significant contribution. One of simple solution for addressing aforementioned problem is to localize the nodes using the Global Positioning System (GPS). But, it is not possible in case of sensor nodes, because GPS leads to increase nodes' size, power consumption and cost. Further, it is noticed that GPS devices are not applicable in indoors applications. As a result, few of nodes associated with GPS, called anchors and rest of nodes are called unknown nodes; these are localized through localization algorithms. Hence, node localization is precondition and foundation for the application of WSNs [8]. Presently, location algorithms are divided into two categories i.e. range-based localization algorithm and range-free localization algorithm [9]. The range-based localization algorithms require high power consumption and cost. But, range-free localization algorithms having low cost and power consumption. Additionally, these algorithms do not require any additional hardware support. Thus, these algorithms are widely adopted in WSNs as localization algorithms [10-12]. Among these, DV-Hop algorithm is one of range-free localization algorithm that can be widely adopted as node localization algorithm in WSNs, but, this algorithm suffers with low accuracy. From literature, it is observed that the localization accuracy of DV-Hop algorithm is improved through other meta-heuristic algorithm such as particle swarm optimization algorithm [13], genetic algorithm [14-15], artificial bee colony algorithm [16] and shuffled frog leaping algorithm [17-18] and so on.

In this work cat swarm optimization algorithm is applied for enhance the performance of DV-Hop algorithm. Tasi et al., have developed CSO algorithm for solving constrained optimization problem in 2006 [19]. The CSO algorithm is based on the haunting skills of cats. This algorithm consists of two modes- seeking mode and tracing mode. Here, CSO algorithm is employed in second phase of DV-Hop algorithm to optimize localization error. The advantages of CSO is simple and easy implementation, more accurate results, computational efficiency and less number of user defined parameters.

Rest of paper is organized as fellows. Section 2 describes the related work. Section 3 summarizes original DV-Hop algorithm. CSO algorithm is explained in section 4. Section 5 describes the proposed improvement in DV-Hop algorithm. Section 6 illustrates the experimental results of study. Section 7 presents the conclusion of entire work.

II. RELATED WORK

This section describes the recent work reported in the field of node deployment for wireless sensor networks. Liu and He have proposed a novel deployment approach, called ACO-Greedy to address the grid-based coverage with low-cost and connectivity-guarantee problem [20]. The objective of proposed approach is to avoid energy hole, decrease deployment cost and improve coverage speed. The simulations results state that the proposed approach provide effective and efficient results from aforementioned problem.

Banimelhem et al., have proposed genetic algorithm based node deployment algorithm for WSNs and also to handle coverage hole problem [21]. It is noticed that the proposed algorithm can optimize the network coverage in terms of the coverage ratio.

Huang et al., have developed an ant colony optimization based node deployment strategy for wireless sensor networks [22]. Experimental results prove that proposed strategy significantly outperform than other state of art algorithms in terms of deployment cost and network lifespan.

Ozdag, and Karci have proposed electromagnetism like algorithm for dynamically deployment of sensor nodes in wireless sensor network environment [23]. In their work, binary detection model is used to compute the coverage rate. The simulation results show that the proposed algorithm provide better results and also an effective algorithm for sensor nodes deployment.

Jiang et al., have developed connected dominating set (CDS) based algorithm for successful deployment of sensor nodes [24]. Authors claim that proposed algorithm have higher coverage rate and less communication and movement energy consumption during deployment.

Liu et al., have proposed a new algorithm based on spatial distribution of soil information in farmland for deploy of sensor nodes [25]. The objective of their proposed approach is to effectively monitor the crop growth with complete coverage. The results demonstrate that proposed approach works efficiently and effectively in precision agriculture.

Huang et al., have developed an ionic bond-directed particle swarm optimization (IBPSO) approach for deploying sensor nodes in sensor field efficiently [26]. It is observed that proposed approach gives more satisfactory results in terms of regional convergence and also provide dynamic deployment of sensor nodes.

To design an efficient node deployment method, Jiang et al., have proposed self-deployment depth adjustment algorithm (SDDA) for under water wireless sensor networks [27]. In proposed algorithm, the connected tree concept is applied. Further, it is noticed that SDDA obtains higher connectivity with different communication ranges and different numbers of nodes than CTDA.

To reduce the cost of sensor nodes deployment, Su et al., have proposed an algorithm based on dynamic ant colony optimization for node deployment in wireless sensor networks [28]. The proposed algorithm includes dynamic heuristic factor, expectations heuristic factor, dynamic evaporation factor and global pheromone updating strategy. The simulation results show that the proposed algorithm provides state of art results in comparison to other algorithms with reduced number of deployed nodes.

To achieve optimal coverage, a Markov chain model based harmony algorithm is employed for deployment of sensor nodes and also to address coverage problem of WSNs [29]. It is observed that proposed algorithm the proposed algorithm can optimize the network coverage in terms of overall coverage ratio and coverage degree.

Wang et al., have proposed a new algorithm for node deployment and coverage optimization strategy for WSNs based on virtual force and glowworm based optimization algorithm [30]. The results demonstrate that proposed algorithm can effectively improve the coverage of sensor nodes and also to overcome redundancy of sensor nodes.

Lai and Fan have proposed an energy balanced node deployment with a balanced energy (END-BE) algorithm for WSNs [31]. The experimental results reveal that proposed algorithm consumes less energy and also improve the network lifetime.

An improved reliability based virtual force algorithm is proposed for addressing the low coverage and deployment of sensor nodes in WSNs [32]. It is observed that IRVFA algorithm better results than RVFA and VFA algorithm in terms of coverage rate, effective utilization of the nodes and network performance.

An enhanced deployment algorithm based on Artificial Bee Colony (ABC) for wireless sensor networks is reported in [33]. The objective of the proposed algorithm is to improve the network life span and reduce the number of deployed relays. The experimental results show that the proposed algorithm considerably improves the network life time and also constraints the deployed relays.

Sun et al., have proposed k-degree coverage algorithm to optimize nodes deployment in WSNs [34]. Authors claim that proposed algorithm obtains better results in comparison to other algorithms in terms of the coverage quality and network lifetime. A Pigeon Swarm Optimization based selfnode deployment algorithm is reported for under water wireless sensor networks [35]. Through experimental results, it is observed that proposed algorithm improves both network connectivity and network reliability, and decreases network deployment energy consumption, and increases network coverage. To deploy the minimum sensor nodes in for achieving agricultural intelligent monitoring based on optimized theory is reported in [36]. In the proposed algorithm, firstly a mathematical model is formed for node location selection. Results reveal that proposed model can perform relevant monitoring tasks with fewer nodes. A localization algorithm based on compressive sensing theory is reported for WSNs [37]. In the proposed approach, nodes are sparse and grid is utilized to compute the locations of nodes. Further, it is observed that proposed algorithm reduces time complexity and also maintain good localization accuracy and efficiency. An algorithm based on area priority concept is proposed for node deployment in WSNs [38]. In the proposed algorithm, initially a satellite image of environment is used for deployment of sensors nodes. Further the K-means algorithm is adopted to cluster the deployed nodes. It is observed that proposed approach outperforms than random deployment of sensor nodes.

III. DV-HOP ALGORITHM

This section describes DV-Hop algorithm in brief. The distance vector based positioning algorithm for mobile ad-hoc network is proposed by Niculescu and Nath in 2003 [39].The implementation of algorithm consists of three steps. The very first step of DV-Hop algorithm consists of broadcasting of beacon packets through anchor nodes in network. This packet contains location information with hop count value which is initialized to zero. When a node received a beacon packet, a table is created for every anchor nodes. This table consists of coordinates of anchor nodes and hop size i.e. (xi ,yi , hopi) where xi , yi represents coordinate of anchor nodes and hopi represents minimum number of nodes from anchor node. If a received packet having less hop count value to a anchor node, hop count value of the table is updated for received packet, and further, packet is forwarded in the network with increased hop count value by 1; otherwise ignored. Through this mechanism, all nodes in the network maintain the minimum hop count value for every anchor node. After obtaining the minimum hop count for other anchor nodes, the second step is to determine the average size of which is computed through equation 1.

$$\mathrm{hopSize}_i = \frac{\sum_{i\neq j}^{N}\sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2}}{\sum_{i\neq j}^{N} h_{ij}} \quad (1)$$

Where, (xi ,yi) and (x j , y j) presents the coordinates of anchor nodesi and j, and hi j is number of hops between anchor nodes i and j. After computing average hop-size, in next step is to broad cast its hop size through each anchor node in network using controlled flooding. When an unknown node obtains hop-size information message, then, itstored only first received message and after that transmits this message to its neighboring nodes. Using this, most of nodes obtain minimum hop-size from anchor nodes and also compute the distance between itself and anchor nodes using equation 2.

$$d_{ij} = \mathrm{hopSize}_{pi} + h_{ij} \quad (2)$$

Where, $\mathrm{hopSize}_{pi}$denotes the average hop-size of unknown node p obtains from the nearest anchor nodei, and hoppk is the minimum number of hops between the unknown node p and the anchor node k.

After computing the distance between unknown nodes and anchor nodes, the next step is to compute the estimated position of unknown nodes using polygon method. Consider, the position (coordinates) of unknown node p is (x, y), position of ith anchor node is (xi ,yi), and distance between anchor nodei and unknown node p is di. Assuming, an anchor node estimate the location of unknown node p, then, the location is estimated through equation 3.

$$\left.\begin{array}{c}(x-x_1)^2+(y-y_1)^2=d_1^2\\(x-x_2)^2+(y-y_2)^2=d_2^2\\\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\\(x-x_n)^2+(y-y_n)^2=d_n^2\end{array}\right\} \quad (3)$$

Hence, to make equations linear, subtracting the last equation from first (n−1) equations, then obtained (n − 1) equations as given in equation 4.

$$\left.\begin{array}{l}x_1^2+y_1^2-x_n^2-y_n^2+2(x_1-x_n)x+2(y_1-y_n)y=d_1^2-d_n^2\\x_2^2+y_2^2-x_n^2-y_n^2+2(x_2-x_n)x+2(y_2-y_n)y=d_2^2-d_n^2\\\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\\x_{n-1}^2+y_{n-1}^2-x_n^2-y_n^2+2(x_{n-1}-x_n)x+2(y_{n-1}-y_n)y=d_{n-1}^2-d_n^2\end{array}\right\} \quad (4)$$

Further, the equation 4 can be rewrite in the form of AX = B, where A, B, and X are described using equations5-7.

$$A = \begin{bmatrix} 2(x_1-x_n) & 2(y_1-y_n) \\ 2(x_2-x_n) & 2(y_2-y_n) \\ . & \\ . & \\ 2(x_{n-1}-x_n) & 2(y_{n-1}-y_n) \end{bmatrix} \quad (5)$$

$$B = \begin{bmatrix} x_1^2 + y_1^2 - x_n^2 - y_n^2 + d_1^2 - d_n^2 \\ x_2^2 + y_2^2 - x_n^2 - y_n^2 + d_2^2 - d_n^2 \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ x_{n-1}^2 + y_{n-1}^2 - x_n^2 - y_n^2 + d_{n-1}^2 - d_n^2 \end{bmatrix} \quad (6)$$

$$X = \begin{bmatrix} x \\ y \end{bmatrix} \quad (7)$$

The location of pth node is computed using equation 8.

$$X = (A'A)^{-1}AB \quad (8)$$

IV. CAT SWARM OPTIMIZATION

CSO algorithm is an evolutionary optimization technique which is applied for searching the best solution by simulating the behavior of cats [19]. In CSO algorithm, positions of the cats represent the potential solution for optimization problems. The objective of CSO algorithm is to derive the best possible direction of the optimal solution by balancing its two modes- seeking mode and tracing mode. The seeking mode describes the curiosity of cats towards the moving objects while tracing mode describes the outstanding hunting skills. A mathematical model is formed by combining these two modes to solve the optimization problems and cats are represented using the position and velocity vectors in a random search space. A problem specific fitness function is used to direct the next step of search. In CSO algorithm, position of cats represents the possible solution set and a flag is used to determine the type of mode of the cat. Recently, CSO algorithm gain wide popularity among research to solve different kinds of optimization problems [40-47].The velocity and position of cat is computed using equation 9-10.

$$V_{i,new} = w * V_i(t) + r * \left(X_{best}(t) - X_i(t)\right) \quad (9)$$

$$X_{i,new} = X_i(t) + V_{i,new} \quad (10)$$

Steps of CSO Algorithm

This section describes the steps of CSO algorithm for clustering. The main steps of the CSO algorithm are given as

Steps of ICSO algorithm

Step 1:	Initialize the different parameters of proposed algorithm like number of cats (N), SMP, SRD, neighborhood structure, β, α and C and randomly placed N number of cats in random space search.
Step 2:	Initialize position and velocity of each cat into the D-dimensional search space.
Step 3:	Compute the fitness function of cats and store the best position of cat into memory.
Step 4:	While($i < maximum\_iteration$)
Step 5:	According Flag value, randomly distributed cats into tracing and seeking modes
Step 6:	If (Flag==1); Cat in seeking mode
Step 7:	For each cat, apply seeking mode process
Step7.1:	Make the j copy of each cat.
Step 7.2:	Compute shifting bit value for each cat using SRD.
Step 7.3:	Add or subtract each cat to shifting value.
Step 7.4:	Compute the fitness function for each new position of cats.
Step 7.5:	Compare the value of fitness function and keep the best position of cat into memory.
Step 7.6:	End for
Step 8:	Else, Cat in tracing mode
Step 9:	For each cat, apply tracing mode process
Step9.1:	Update the velocity of each cat using equation 3.
Step9.2:	Update the position of each cat using equation 4.
Step9.3:	Compute the fitness function for newly generated position of cat.
Step9.4:	Compare the fitness function value and keep the best position of cat into memory.
Step9.5:	End for
Step 10:	Update the position of cats and also determine best position of cat.
Step 11:	End while
Step 12:	Obtain the final solution.

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 5, Issue 1, January 2018

V. PROPOSED ALGORITHM

This section describes CSO based DV-Hop algorithm for optimizing localization error in second step of original DV-Hop algorithm. In DV-Hop algorithm, an error can occur when compute the estimated distance between unknown nodes and anchor nodes. Hence, to optimize this error is one of important issue for improving the performance of the localization algorithm. Large numbers of evolutionary algorithm are reported in literature for solving optimization problems. Hence, in this work, CSO based optimization algorithm is adopted for reducing error rate of DV-Hop algorithm. In literature, it is observed that many researchers have applied evolutionary algorithm for reducing the error rate of DV-Hop algorithm.

A. Hop Size Improvement

In DV-Hop algorithm, average hop sizeis calculated using equation 1and possible contains some error extent.Let us consider that the average hop size for each anchor node is equal to $\mathrm{hopSize_i}$The actual distance between two anchor nodes i and j is denoted using dij which is computed using equation 2. The error between dij and the estimated distance which is computed using $\mathrm{hopSize_i}$is illustrated using hij that denotes the number of hops between two anchor nodes i and j. So, in our proposed algorithm, the CSO algorithm is adopted to optimize the results of first step of DV-Hop, so, the CSO algorithm is applied on the second step of DV-Hop algorithm to reduce the error of determined hop sizes. The fitness function is described in terms of eij which is correspond to error between real and estimated distance between anchor nodes i and j. The minimization of fitness function eij is corresponds to better estimation of hop size value for each anchor node. The fitness function can be expressed as given below.

$$f(\mathrm{hopsize_i}) = \frac{1}{N-1}\sum_{i\neq j}^{N}\frac{d_{ij}}{h_{ij}}e_{ij}^2 \qquad (11)$$

It also observed that anchor nodes have not equal effects on the error. So, in this work, a weight matrix (W) is computed for each anchor nodes from unknown nodes. This weight matrix is determined using equation 12.

$$W = \begin{bmatrix} w_{p,1} & 0 & .. & 0 \\ 0 & w_{p,2} & .. & 0 \\ ... & .. & & ... \\ 0 & 0 & & w_{p,n-1} \end{bmatrix} \qquad (12)$$

Where, $w_{p,1}$is the weight of the unknown node p for ith anchor node and can be computed using equation 13.

$$w_{p,1} = \frac{d_{ij}}{h_{ij}} \qquad (13)$$

After determination the value of fitness function, the CSO algorithm is presented. In CSO algorithm, population of cats is described using hop size and each cat considers only one single parameter. Initially, populations of cats are randomly defined using hop size to find better optimal solution. Further, the CSO algorithm is utilized for optimizing average hop size and the best cat position can be considered as a new hop size. The flow chart of the proposed CSO based DV-Hop algorithm is illustrated in Fig. 1.

VI. EXPERIMENTAL RESULTS

A. Simulation environment

This subsection describes the simulation environment of CSO DV-Hop algorithm. The proposed algorithm is implemented in MATLAB environment on window based operating system using 2.20 GHz Intel Core i7 CPU and 8 GB RAM. A 100x 100 sensor field is considered to deploy 100 sensor nodes randomly. The squares nodes represent the anchor nodes whereas circle nodes represent anchor nodes. The communication range of each node is set to 60. The maximum number of iteration is set to 50. The results are taken as the average of twenty five independent runs. The performance of the algorithm is tested on average localization error which is computed using equation 14.

$$\text{Average Error} = \frac{\sum_{i=1}^{M}\sqrt{(x_{estmitaed}-x_i)^2+(y_{estimated}-y_i)^2}}{M} \qquad (14)$$

Where, M is the number of unknown nodes, R is communication range, (xestimated, yestimated) is the estimated coordinate of unknown node i and (xi, yi) is the actual coordinate of unknown node. Further, the experimental results of the proposed algorithm are compared with DV-Hop algorithm, SFLA DV-Hop, GA DV-Hop, PSO DV-Hop algorithms [39, 17, 18].

ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 5, Issue 1, January 2018

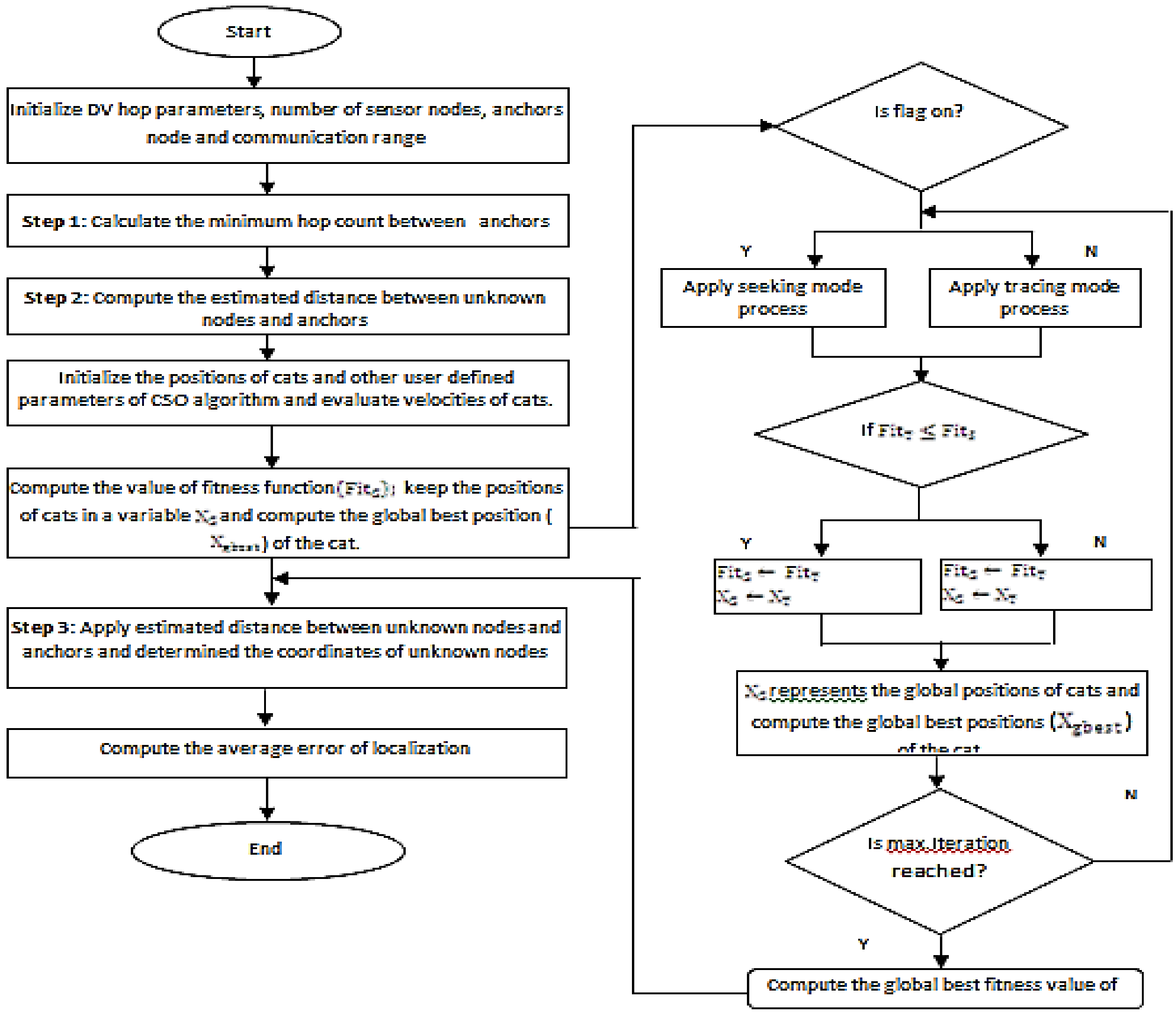

Fig. 1: Flow chart of proposed CSO based DV-Hop algorithm

B. Effects of number of anchor nodes on positioning accuracy

Fig. 2 shows the results of proposed CSO DV-Hop algorithm and rest of algorithms being compared using average localization error and different number of anchor nodes. The range of anchor nodes varies in between 10% to 50%. It is observed that the average error rate is decreasing as the number of anchor nodes increased. Further, it is also noticed that proposed algorithm obtains low error rate among all other algorithms being compared. It is noted that due to increment in number of anchor nodes, hop count between anchor nodes and unknown nodes become decreased and in turn resulted into reduce accumulated error of estimated distance between anchor nodes and unknown nodes.

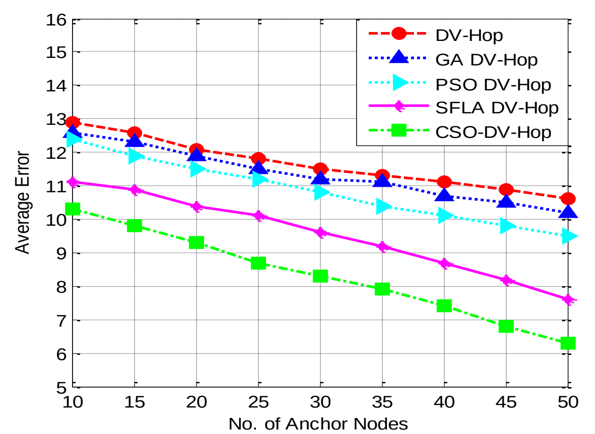

Fig. 2: Average localization error of unknown nodes at different number of anchors

C. Effects of communication range on positioning accuracy

Fig. 3 depicts the results of average localization error of proposed algorithm, DV-Hop algorithm, SFLA DV-Hop, GA DV-Hop and PSO DV-Hop algorithms using communication range. The communication range of each node varies in the range 30 to 60. It is noted that number of sensor nodes and the number of anchor nodes are equal to 100 and 10 respectively. It is observed that error is increased when communication range increases for all algorithms. It is due increment in the hop size. But, it reveals that the proposed algorithm provides less average localization error among all algorithms. It is also noted that when communication range increases, then the performance of PSO DV-hop and SFLA DV-Hop algorithms is almost same.

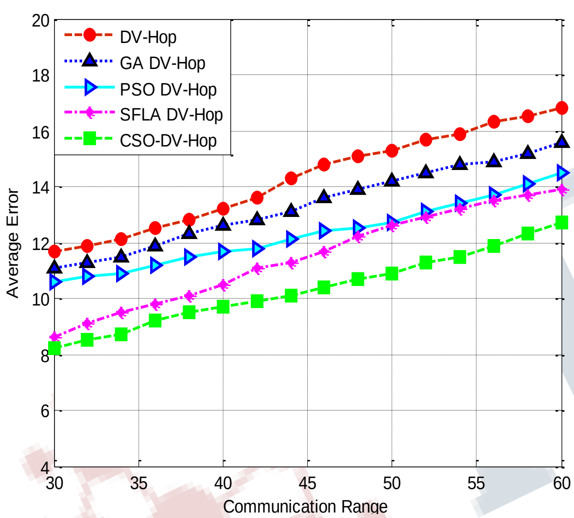

Fig. 3: Average localization error of unknown nodes with the change of communication range

D. Effects of number of sensor nodes on positioning accuracy

Fig. 4 shows the results average localization error of all algorithms using increase number of sensor nodes. The numbers of sensor nodes in network are ranges in between 100 to 300 and communication range is set 60. Further, the number of anchors is set to 10% of total nodes. The density of network becomes dense due to increment in number of nodes. It is observed that as the density of network is increased, the number of hops decreased and in turn resulted into more accurate average ho size. Hence, the average localization error can decrease. It is also observed that the proposed algorithm gives better results in comparison to other algorithms being compared

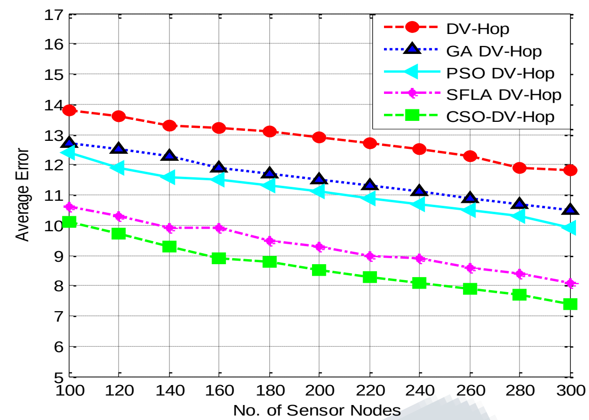

Fig. 4: Average localization error of unknown nodes with the change of total nodes

E. Execution time

Execution time of all algorithms is also computed and can be considered as one of performance parameters to evaluate the performances of algorithms. Table 1 summarizes the execution time of each algorithm. The number of anchors is set to 10 % of the total numbers of nodes. From this table it is noticed that original DV-Hop algorithm take less time in execution with different number of sensor nodes. Whereas, GA DV-hop algorithm takes larger time to converge among all algorithms being compared. It is also observed that CSO DV-Hop algorithm takes more time for convergence in comparison to DV-Hop, SFLA DV-Hop and PSO DV-Hop. But, the results of proposed algorithm with rest of parameters are better than all other algorithms. Further, it is also observed that as the numbers of sensor nodes increase, the computational times of all algorithm increases.

Table 1: Average computational times of proposed algorithm and other algorithms being compared.

Algorithms	Number of Sensor Nodes			
	100	150	200	300
DV-Hop	0.05786	0.09235	0.1256	0.3562
SFLA DV-Hop	4.8752	7.8635	9.5673	11.9242
GA DV-Hop	8.7312	15.9543	20.0374	24.1457
PSO DV-Hop	4.2563	6.4582	8.7361	10.589
CSO DV-Hop	8.9132	14.5621	18.6187	21.1506

VII. CONCLUSION

In wireless sensor networks, locations of sensor nodes have significant impact on its performance in many applications areas. In this work, CSO algorithm is adopted to reduce the localization error of DV Hop algorithm. . The CSO algorithm is applied in the second phase of DV-Hop to reduce average localization error, called CSO DV-Hop algorithm. Further, a weight matrix is also considered for each anchor node to normalize the impact of anchor nodes on error extent. The effectiveness of the proposed algorithm is evaluated using three different scenarios i.e. number of anchor nodes, communication range and number of sensor. The results of proposed CSO DV-Hop algorithm are compared with some other improved version of DV Hop algorithms. From the experimental results, it is stated that the proposed algorithm obtains minimum average localization error in comparison to all other algorithms using all scenarios. Further, computational time is also taken as performance parameter. It is observed that proposed algorithm take more computation time in comparison to DV-Hop, PSO DV-Hop and SFLA DV-Hop algorithms. But, it is observed that the proposed CSO DV-Hop algorithm have significant advantage of all other algorithms being compared. Further, it is concluded that CSO DV-Hop algorithm is effectively handle the localization issue of WSNs.

REFERENCES

1. Tomic, S., &Mezei, I. (2016). Improvements of DV-Hop localization algorithm for wireless sensor networks. Telecommunication Systems, 61(1), 93–106.

2. Yick, J., Mukherjee, B., &Ghosal, D. (2008).Wireless sensor network survey. Computer Networks, 52(12), 2292–2330.

3. Mesmoudi, A., Feham, M., &Labraoui, N. (2013). Wireless sensor networks localization algorithms: A comprehensive survey.International Journal of Computer Networks and Communications (IJCNC), 5(6), 45–64.

4. Yang, X., Zhang, W., & Song, Q. (2015). An improved DV-Hop algorithm based on shuffled frog leaping algorithm. International Journal of Online Engineering, 11.

5. Lee, S.-M., Cha, H., & Ha, R. (2007). Energy-aware location error handling for object tracking applications in wireless sensor networks. Computer Communications, 30(7), 1443–1450.

6. Pensas, H., Raula, H.,&Vanhala, J. (2009). Energy efficient sensor network with service discovery for smart home environments. In Third international conference on sensor technologies and applications, 2009 (SENSORCOMM'09). IEEE.

7. Chen,Y., et al. (2010).Asmart gateway for health care system using wireless sensor network. In 2010 fourth international conference on sensor technologies and applications (SENSORCOMM).IEEE.

8. Niclescu, D., N. L. America. Communication Paradigms for Sensor Network. – IEEE Communications Magazine, Vol. 43, 2005, No 3, pp. 116-122.

9. Sun, L., J. Li, Y. Chen. Wireless Sensor Networks. Tsinghua University Press, Beijing, 2005, pp. 45-50.

10. Arivubrakan P., V. R. S. Dhulipala. Energy Consumption Heuristics in Wireless Sensor Networks. – In: Proc. of IEEE International Conference on Computing, Communication and Applications, Din Digul, Tamilnadu, 2012, pp. 1-3.

11. Ji, B., L. Wang, Q. Yang. New Version of AES-ECC Encryption System Based on FPGA in WSNs. – Journal of Software Engineering, Vol. 9, 2015, No 1, pp. 87-95.

12. Arivubrakan, P., V. R. S. Dhulipala. Sentry Based Intruder Detection Technique for Wireless Sensor Networks. – Journal of Artificial Intelligence, Vol. 6, 2013, No 2, pp. 175-180.

13. Huang, Y., C.-Z., Zang, H.-B. Yu. Localization Method Based on Modified Particle Swarm Optimization for Wireless Sensor Networks. – Control and Decision, Vol. 27, 2012, No 1, pp. 156-160.

14. Zhang, W., Q. Song. An Improved DV-Hop Algorithm Based on Genetic Algorithm. – Journal of Chongqing University, Vol. 38, 2015, No 3, pp. 162-169.

15. Ren, W., & Zhao, C. (2013). A localization algorithm based on SFLA and PSO for wireless sensor network. Information Technology Journal, 12(3), 502.

16. Li, M.-D., W. Xiong, L. Guo. Improvement of DV-Hop Localization Based on Artificial Bee COLONY Algorithm. – Computer Science, Vol. 40, 2013, No 1, pp. 33-36.

17. Ge, Y., X.-P. Wang, J. Liang. Improvement of DV-Hop Localization Based on Shuffled Frog Leaping Algorithm, Journal of Computer Applications, Vol. 31, 2011, No 4, pp. 922-924, 1002.

18. Peng, Bo, & Li, Lei. (2015). An improved localization algorithm based on genetic algorithm in wireless sensor networks. Cognitive Neurodynamics, 9(2), 249–256.

19. Chu, S. C., Tsai, P. W., & Pan, J. S. (2006, August). Cat swarm optimization. In Pacific Rim International Conference on Artificial Intelligence (pp. 854-858). Springer Berlin Heidelberg.

20. Liu, X., & He, D. (2014). Ant colony optimization with greedy migration mechanism for node deployment in wireless sensor networks. Journal of Network and Computer Applications, 39, 310-318.

21. Banimelhem, O., Mowafi, M., & Aljoby, W. (2013). Genetic algorithm based node deployment in hybrid wireless sensor networks. Communications and Network, 2013.

22. Huang, G., Chen, D., & Liu, X. (2015). A node deployment strategy for blindness avoiding in wireless sensor networks. IEEE Communications Letters, 19(6), 1005-1008.

23. Özdağ, R., & Karcı, A. (2015). Sensor node deployment based on electromagnetism-like algorithm in mobile wireless sensor networks. International Journal of Distributed Sensor Networks.

24. Jiang, P., Liu, J., Wu, F., Wang, J., & Xue, A. (2016). Node deployment algorithm for underwater sensor networks based on connected dominating set. Sensors, 16(3), 388.

25. Liu, N., Cao, W., Zhu, Y., Zhang, J., Pang, F., & Ni, J. (2015). The node deployment of intelligent sensor networks based on the spatial difference of farmland soil. Sensors, 15(11), 28314-28339.

26. Huang, H., Zhang, J., Wang, R., & Qian, Y. (2014). Sensor node deployment in wireless sensor networks based on ionic bond-directed particle swarm optimization. Appl. Math, 8(2), 597-605.

27. Jiang, P., Wang, X., & Jiang, L. (2015). Node deployment algorithm based on connected tree for underwater sensor networks. Sensors, 15(7), 16763-16785.

28. Su, H., Wang, G., Sun, X., & Yu, D. (2016). Optimal node deployment strategy for wireless sensor networks based on dynamic ant colony algorithm. International Journal of Embedded Systems, 8(2-3), 258-265.

29. Mohsen, A., Aljoby, W., Alenezi, K., & Alenezi, A. (2016). A robust harmony search algorithm based Markov model for node deployment in hybrid wireless sensor networks. Int. J., 11(27), 2747-2754.

30. Wang, J., Cao, Y., Cao, J., Ji, H., & Yu, X. (2016, December). Virtual Force and Glowworm Swarm Optimization Based Node Deployment Strategy for WSNs. In International Conference on Computer Science and its Applications (pp. 456-462). Springer Singapore.

31. Lai, W. K., & Fan, C. S. (2017). Novel Node Deployment Strategies in Corona Structure for Wireless Sensor Networks. IEEE Access, 5, 3889-3899.

32. Teng, Z. J., Xu, M. M., & Zhang, L. (2016). Nodes deployment in wireless sensor networks based on improved reliability virtual force algorithm. Journal of Northeast Dianli University, 36(2), 86-89.

33. Hashim, H. A., Ayinde, B. O., & Abido, M. A. (2016). Optimal placement of relay nodes in wireless sensor network using artificial bee colony algorithm. Journal of Network and Computer Applications, 64, 239-248.

34. Sun, Z., Li, C., Xing, X., Wang, H., Yan, B., & Li, X. (2017). k-degree coverage algorithm based on optimization nodes deployment in wireless sensor networks. International Journal of Distributed Sensor Networks, 13(2), 1550147717693242.

35. Yu, S., Xu, Y., Jiang, P., Wu, F., & Xu, H. (2017). Node Self-Deployment Algorithm Based on Pigeon Swarm Optimization for Underwater Wireless Sensor Networks. Sensors, 17(4), 674.

36. Sai, Z., Fan, Y., Yuliang, T., Lei, X., & Yifong, Z. (2016). Optimized algorithm of sensor node deployment for intelligent agricultural monitoring. Computers and Electronics in Agriculture, 127, 76-86.

37. Wei, Y., Li, W., & Chen, T. (2016). Node localization algorithm for wireless sensor networks using compressive sensing theory. Personal and Ubiquitous Computing, 20(5), 809-819.

38. Ateş, E., Kalayci, T. E., & Uğur, A. (2017). Area-priority-based sensor deployment optimisation with priority estimation using K-means. IET Communications.

39. Niculescu, D., &Nath, B. (2003). DV based positioning in ad hoc networks. Telecommunication Systems, 22(1–4), 267–280.

40. Panda, G., Pradhan, P. M., & Majhi, B. (2011). IIR system identification using cat swarm optimization. Expert Systems with Applications, 38(10), 12671-12683.

41. Wang, Z. H., Chang, C. C., & Li, M. C. (2012). Optimizing least-significant-bit substitution using cat swarm optimization strategy. Information Sciences, 192, 98-108.

42. Tsai, P. W., Pan, J. S., Chen, S. M., & Liao, B. Y. (2012). Enhanced parallel cat swarm optimization based on the

Taguchi method. Expert Systems with Applications, 39(7), 6309-6319.

43. Kumar, G. N., & Kalavathi, M. S. (2014). Cat swarm optimization for optimal placement of multiple UPFC's in voltage stability enhancement under contingency. International Journal of Electrical Power & Energy Systems, 57, 97-104.

44. Kumar, Y., & Sahoo, G. (2016). A hybridise approach for data clustering based on cat swarm optimisation. International Journal of Information and Communication Technology, 9(1), 117-141.

45. Kumar, Y., & Sahoo, G. (2015). A hybrid data clustering approach based on improved cat swarm optimization and K-harmonic mean algorithm. Ai Communications, 28(4), 751-764.

46. Kumar, Y., & Sahoo, G. (2017). Gaussian cat swarm optimisation algorithm based on Monte Carlo method for data clustering. International Journal of Computational Science and Engineering, 14(2), 198-210.

47. Kumar, Y., & Sahoo, G. (2014). A Hybrid Data Clustering Approach Based on Cat Swarm Optimization and K-Harmonic Mean Algorithm. Journal of Information and Computing Science, 9(3), 196-209.