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3D localization of moving target nodes using single anchor node in anisotropic wireless sensor networks

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ABSTRACT

In this paper, novel 3D node localization algorithms using applications of Computational Intelligence (CI) for moving target nodes are attained using single reference node (anchor node) in an anisotropic network. Target nodes are randomly deployed at beneath and middle layers. Whereas single anchor node is deployed at top layer. Recent applications of Computational Intelligence (CI), i.e., Particle Swarm Optimization (PSO), H-Best Particle Swarm Optimization (HPSO), Biogeography Based Optimization (BBO) and Firefly Algorithm (FA) are used respectively to estimate the optimum location of moving target nodes. In this paper, each target node has heterogeneous properties (due to different battery backup statuses). Degree of Irregularity (DOI) of 0.01 is considered for radiation pattern. In heterogeneous network, the geometric distance between two nodes is not proportional to their hop count. Once a moving target falls under the range of a deployed anchor node, three virtual anchor nodes (minimum 4 anchor nodes are required for 3D positions) in surrounding of anchor and respective moving target node are projected by using umbrella projection form to find the 3D position. The proposed algorithms are designed for rescue operations in highly hostile environment.

1. Introduction

Wireless Sensor Networks (WSNs) have appeared as a key tool for many applications including environmental monitoring, disaster relief, transportation, industrial monitoring, target tracking and many more [1]. A Wireless Sensor Network (WSN) consists of an array of sensors (either homogenous or heterogeneous) deployed in respective field to retrieve the relevant information [2]. The core function of WSNs in most of the applications is to detect and report about events, which can be meaningfully detailed if the precise locations of the occurring event and reporting nodes are known. Location attainment of the target node in WSNs is one of the gigantic tasks and referred as localization problem. Accomplishment of three dimension (3D) position is more challenging particularly in anisotropic networks (due to different battery backup statuses, non uniform radiation pattern and DOI). In Radio Irregularity Model (RIM), the parameter name Variance of Sending Power (VSP) defined as the maximum percentage variance of the signal sending power among different devices is considered [3]. The signal sending power is modeled by $VSP = SendingPower \times (1 + Rand \times VSP)$. Where *Rand* is used to generate uniformly distributed random values between 0 and 1.

To locate a node in 2D/3D coordinate system of WSN, some special nodes (Anchor Nodes) [4] are required that are aware of their positions in advance by virtue of being manually placed or by equipping a Global Positioning System (GPS). The other unknown nodes (target nodes) estimate their positions by using some localization algorithms. Manual configuring or equipping each node with Global Positioning System (GPS) is a complex and less feasible task due to high cost and deployment limitations. Node localization can be done in two steps, i.e., distance measurement and geometric calculation. Range based localization and range free localization are the sub division of the distance measurement based localization techniques. In range based localization, the distance estimation between two nodes can be estimated by Received Signal Strength Indicator (RSSI) [5,6], Time of Arrival (ToA), Time Difference of Arrival (TDoA) and Angle of Arrival (AoA) [7]. Range free localization scheme assumes isotropic networks where the distance between nodes is directly proportional to their hop counts. Distance Vector Hop (DV-Hop), Multi dimensional Scaling (MDS) and Ad-Hoc Positioning (APS) are the some of the range free techniques thet provides position of target nodes with fewer infrastructures. In WSNs, fully static deployment can never be envisioned; Mobile Wireless Sensor Networks (MWSNs) are much more flexible than static sensor networks as they can be deployed in any scenario and survive with change in their respective topology. Connectivity, coverage and energy

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consumption are the critical challenges that needed to be overcome in mobility based deployment. One of the most significant challenge in MWSNs is need for accurate localization of target node. The assumptions taken for 2D are violated in space, atmospheric and underwater applications where network height is utmost required. Also for these kind of applications, nodes are randomly distributed in three dimensional space. The nodes are deployed at different depths in underwater sensor network and better forecast monitoring can be done by deploying nodes at 3D space in the atmosphere.

In this paper, a novel idea of virtual anchor nodes have been proposed with umbrella projection around moving target nodes to evaluate the 3D positions in an anisotropic environment using application of Particle Swarm Optimization (PSO), H-Best Particle Swarm Optimization (HPSO), Biogeography Based Optimization (BBO) and Firefly Algorithm (FA). Only single anchor node is used as a reference (anchor) node to localize the moving target node in the 3D network. In this paper, authors have considered a highly chaotic cubic structure with three layer environment and heterogeneous properties of the nodes. Target nodes are randomly deployed over the second and third layers that are moving in the random fashion. Once a moving target node falls under the range of deployed anchor node, three virtual anchor nodes (minimum four anchor nodes are required for 3D static position) in surrounding (anchor and respective moving target node) are projected with umbrella projection to find the 3D position. In proposed algorithms, problem of Line of Sight (LoS) is minimized due to projection of virtual anchor nodes.

The rest of the paper is organized as follows: Literature review on WSNs localization is presented in Section 2. Section 3 ushers the readership into outline of PSO, HPSO, BBO and FA used for localization in this paper. This is followed with Implementation of above said algorithms in Section 4. Simulation results are discussed in Section 5. Finally, conclusions and an outcrop on possible future research path are presented in Section 6.

2. Literature review

WSN consists of a multi-hop and self configured network composed by large number of sensor nodes (either homogeneous and heterogeneous). Each node in network collects, computes and communicates the information to its neighbor node and further transfer to the sink node. The information collected and communicated by a sensor node is meaningless without knowing the accurate location of the respective node. Manual embedding the location information to each node is very tedious job and even not feasible in many applications. So, low cost localization become a key technology in WSNs. Currently, the main focus of localization approaches is on two dimensional (2D) planes. However, 3D localization algorithms are required for the networks in which nodes are actually deployed in the 3D scenarios like deep sea, forest, hills and space. Although, the 3D environment is more complicated than 2D environment but with some exceptions the algorithms used for 2D localization can be directly extended to 3D localization.

Bulusu et al. [8] addressed localization algorithms for unconstrained open-air environments for tiny low-cost devices without using GPS. The authors characterized existing localization techniques and explored an RF-based localization method in which receiver localizes itself using Centroid method of localization. Graefenstein et al. [9] proposed an energy efficient mobile anchor based localization technique in which the distance between anchor and target nodes is calculated using RSSI and further trilateration algorithm is applied for localization. Sumathi and Srinivasan [10] proposed an algorithm in which a single anchor is used for localization with RSS measurement. In this paper, least square method is used for localizing the static target nodes. Guo et al. [11] proposed a mobile assisted Perpendicular Intersection (PI) based localization technique which has no direct mapping of distances from RSS values. Node position computation is done by utilizing the geometric relationship of PI. Shi et al. [12] proposed UWB TOA (Ultra Wide Band, Time of Arrival) technique for ranging in the process of 3D node localization. The authors suggested that the distance between anchor and target node can be measure more precisely by using this technique. Wang et al. [13] proposed a DV-Hop based 3D node localization algorithm which can effectively localize the sensor node in 3D environment. Computational complexity and high cost are the major drawbacks of this algorithm. Xu et al. [14] proposed an improved algorithm for 3D localization in which degree of coplanarity has introduced with DV-Distance method and further, Quasi-Newton method is used for optimization. Authors verified the effect of proposed algorithm by considering localization accuracy and coverage. Li et al. [15] proposed a localization algorithm for 3D WSNs based on differential RSS irregular transmission model. Authors proposed a new radio model to obtain the numerical relation between DOI and the variation of signal transmission ranges. Ahmad et al. [16] proposed a 3D localization algorithm based on parametric loop division algorithm. In this scheme, the localization of a sensor node is done in a region bounded by a network of anchor nodes. The proposed scheme gives better localization accuracy due to shrinking of network region towards its center point.

CI applications are widely used to get an optimum position of target nodes. Genetic Algorithms (GA) and other stochastic optimization algorithms are available in the literature for static 2D and 3D scenarios. Gopakumar and Jacob [17] proposed a novel and computationally efficient swarm intelligence based global optimization method for localizing static nodes. Mean square range error is considered as the objective function and PSO is used to minimize the error of objective function without being trapped in local minima. Easy implementation and low memory requirement are the advantages of this method. Chuang and Wu [18] presented a PSO based effective node localization technique using RSS ranging. The proposed scheme have higher localization success rate. Li and Bin Wen [19] proposed an efficient two-phase distributed PSO algorithm by which flip ambiguity problem can be reduced. In this algorithm, the initial search space is defined by bounding box method and flip ambiguity is reduced in the refinement phase. Kumar et al. [20] proposed algorithms by using applications of H-Best PSO and BBO techniques for estimating the optimum location of randomly deployed target nodes. HPSO algorithm gives mature and fast convergence and BBO algorithm gives high accuracy and slow convergence. Sujatha and Siddappa [21] proposed a hybrid localization algorithm i.e., Differential Evolution (DE) algorithm along with Dynamic Weight Particle swarm optimization (DWPSO) for obtaining better localization accuracy. The proposed algorithm gives less localization error, high localization accuracy and better stability performance. Kumar et al. [22] also proposed a range free localization techniques based on the applications of HPSO and BBO, without using extra hardware. These techniques are termed as Range Free HPSO (RF-HPSO) and Range Free BBO (RF-BBO). Further, Edge weights are modeled by Fuzzy Logic System (FLS) between anchor and target nodes, considered to estimate the location of target node. The edge weights are further optimized by using the applications of PSO and BBO. Arora and Singh [23] proposed a metaheuristic nature inspired Butterfly Optimization Algorithm (BOA) for optimized localization of unknown sensor nodes. The performance of the proposed algorithm is compared with performance of PSO and FA in 2D scenario. The authors conclude that BOA outperforms other algorithms used in the study in terms of accuracy and computing time.

The range based methods are widely used in localization of sensor nodes due to high accuracy but a primary problem of range based methods is flip ambiguity. The various researchers have suggested various strategies/frameworks to address this important issue [24–27]. The methods proposed in this paper for localization have the following advantages.

- A novel idea of projecting virtual anchor nodes using umbrella structure projection for localizing the 3D moving target nodes is

proposed in an anisotropic environment using applications of PSO, HPSO, BBO and FA. By using these techniques, localization is done by using single anchor node.
- The problem of LOS (Line of Sight) can be minimized by using this techniques.
- The problem of flip ambiguity is refined.

3. CI based location optimization algorithms for WSNs

3.1. Particle Swarm Optimization (PSO) and H-Best Particle Swarm Optimization (HPSO)

A Number of issues in WSNs are formulated as multidimensional optimization problems, and these issues can be approached through CI based optimization techniques. Particle swarm optimization (PSO) is an undemanding, effective and computationally proficient optimization algorithm which was developed by Kennedy and Eberhart [28] in 1952. PSO represents the social behavior of a flock of birds, which consists of a swarm of 's' candidate solutions called particles. These particles explore the n dimensional hyperspace in search of the global solution. PSO technique employs a set of feasible solutions within a search space by allowing each individual to learn from the experience of their own and neighbor location. These particles are randomly located in the search space and the objective function is calculated corresponding to these randomly positioned particles. Each particle is induced to move towards the best position and collects its particle best (pBest) and globally best (gBest) position in the space by obeying rules inspired by bird flocking and fish schools behavior to find better position. Due to involvement of less number of computations, The *gBest* model has the quality of faster evolution due to less computations but there is the threat to be trapped in local minima. To improve localization accuracy, the swarm is divided into sub swarms and the best position experienced by a particle in a sub swarm is called local best (lBest). The *lbest* model has the quality of fast and mature convergence [20]. The PSO variant having *lbest* model, i_{th} particle belonging to a sub-swarm attracts towards the previous *pbest* location p_i, its local sub-swarm *lbest* location p_l and its overall best global *gbest* location p_g within the sub-swarm.

Consider a D-dimensional search space and i_{th} particle within a sub-swarm is represented as $X_i = [x_{i1}, x_{i2}, ..., x_{iD}]$ and its velocity is represented by $V_i = [v_{i1}, v_{i2}, ..., v_{iD}]$. The best position ever visited by an particle is $P_i = [p_{i1}, p_{i2}, ..., p_{iD}]$.

The whole swarm is divided into sub-swarms in *lbest* model based HPSO algorithm, let the particle local best position of each sub-swarm be $P_l = [p_{l1}, p_{l2}, ..., p_{iD}]$ and overall globally best particle is denoted by $P_g = [p_{g1}, p_{g2}, ..., p_{gD}]$, where l and g are particle indices. The particle iterates in every unit time according to (1) and (2)

$$v_{id} = wv_{id} + c_1r_1(p_{id} - x_{id}) + c_2r_2(p_{gd} - x_{id}) + c_3r_3(p_{ld} - x_{id}) \tag{1}$$

$$x_{id} = x_{id} + v_{id} \tag{2}$$

where w is denoted by inertia weight and c_1, c_2 and c_3 are learning parameters. The value of $w = 0.7$ and the value of $c_1 = c_2 = c_3 = 1.4$ were recommended for fast convergence (for more details and flow chart, reader may refer [22,20]).

3.2. Biogeography based optimization

Similar to the well known PSO, The biological populations based algorithm BBO was developed. Biogeography is basically the study of geometrical distribution of biological organisms [29]. The characterization of various species living in different habitats can be done by Habitat Suitability Index (HSI). High HSI means a habitat is suitable place for species to live, whereas, low HSI corresponds to lesser appropriate place for the species to live. vegetation diversity and climate are the factors which can influence the HSI. suitability index vector (SIV) for each habitat can be determine by using these factors. SIV is the characterization of the features of the habitat.

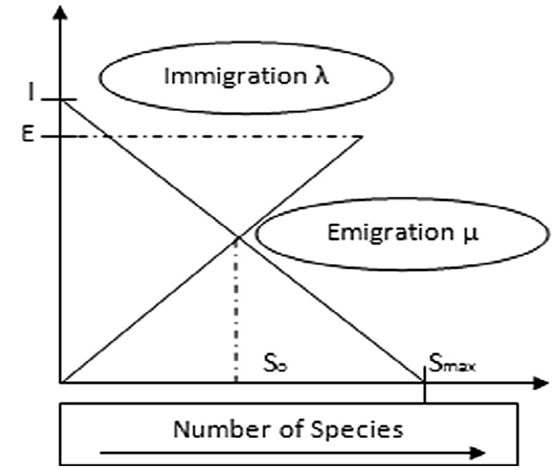

Fig. 1. Immigration and emigration rate with respect to number of species.

The immigration and emigration rates depend upon the number of species in the habitats. These relationships are shown in Fig. 1. Low HSI Habitat has high immigration λ and habitat with high HSI has high emigration μ [20]. The values of immigration and emigration rates are given by Eqs. (3) and (4)

$$\lambda = I\left[I - \frac{k}{n}\right] \tag{3}$$

$$\mu = \frac{E}{n} \tag{4}$$

where I and E is the maximum possible immigration and emigration rates, where I is not necessarily equal to E. k is the number of species of the k_{th} individual and n is the number of species. S_{max} is maximum number of species in a habitat.

3.3. Firefly algorithm

In firefly algorithm (FA), each firefly represent the potential solution of the problem. FA was developed by Dr. Xin-She Yang [30] in 2009, which uses the flash light nature of the fireflies. There are some ideal behavioral rules of fireflies which can be represented as:

- All fireflies are unisex in nature. One firefly travel towards another brighter firefly despite of sex [31].
- Attractiveness is proportional to brightness and inversely proportional to distance. If there is no brighter firefly found, the firefly movement will be random in nature.
- The brightness of the firefly represents individual fitness.

In FA, minimization of error is considered as the objective function. In each iteration less brighter i_{th} firefly moves towards the j_{th} brighter firefly and the position of each firefly is updated, termed as attractiveness. The attractiveness function is given by (5). For $m \gg 1$

$$A(d) = A_0 \cdot exp(-\gamma d^m) \tag{5}$$

In (5), d is the distance between two fireflies, A_0 is the initial attractiveness at $d = 0$ and γ is the absorption coefficient that controls the light intensity. m is the number of local optima.

The distance between i_{th} firefly and j_{th} firefly can be calculated by (6). When the distance increases, the attractiveness tends to decrease.

$$d_{ij} = \sqrt{(a_i - a_j)^2 + (b_i - b_j)^2} \tag{6}$$

The movement process is given in (7), where i_{th} firefly moves towards j_{th} firefly. When i_{th} firefly finds the brighter j_{th} firefly, it starts moving towards j_{th} firefly and achieves the desired convergence.

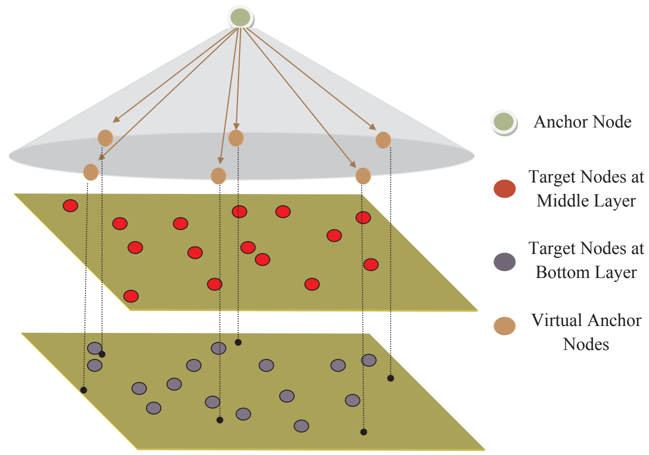

Fig. 2. Umbrella projection of virtual anchor nodes to localize moving target nodes.

$$m_i^{k+1} = m_i^k + A_0 \cdot exp(-\gamma d^2) \cdot (a_j^k - a_i^k) + \alpha \cdot rand_i^k \quad (7)$$

where m_i^k is the i_{th} firefly position at the k_{th} iteration, $A_0 \cdot exp(-\gamma d^2) \cdot (a_j^k - a_i^k)$ is the attractiveness towards j_{th} firefly of i_{th} firefly and $\alpha * rand_i^k$ is the random movement of i_{th} firefly (α is the randomizing coefficient).

4. Optimized node localization using single anchor node

As discussed above, only single anchor node is used to find the positions of moving target nodes. Target nodes are randomly deployed in the two layers of sensing field. The Anchor node is positioned at the top layer whereas, target nodes are randomly deployed at middle and bottom layer of the sensing field.

Algorithm 1. Pseudo code for Umbrella Projection

for Particular target node **do**
  Distance calculation between Anchor and Target node using RSS measures
  Project six virtual anchor nodes at a distance equivalent to above calculated distance with a angle difference of 60 degrees
  Anchor and three virtual anchor nodes (for particular target) will be selected for calculating the centroid and further implementation of the algorithm is done by deploying particles around the centroid ($X_{centroid} + radius \cdot cos\theta, Y_{centroid} + radius \cdot sin\theta, Z_{centroid} + radius \cdot cos\theta \cdot sin\theta$)
end for

Algorithm 2. Pseudo code for Localization by Umbrella Projection

Random Deployment of Target Nodes at middle and bottom layers
Deploy anchor node at the top layer
for Movement Number Starts for target nodes **do**
  for Number of Target Nodes **do**
    Distance calculation between Anchor and Target nodes using RSS measures
    for Target nodes in Range **do**
      Projection of Virtual anchor nodes at the distance equal to Anchor and in-range particular target node
      if Number of Anchor and Virtual anchor nodes $\geqslant 4$ **then**
        Centroid is calculated
        Deploy particles around the centroid at a radius of 1 Unit.
        Apply PSO, HPSO, BBO and FA based optimization Algorithm using objective function
        Calculate the distance error between actual node coordinates and estimated node coordinates
      end if
    end for
  end for
end for

The main responsibility of the anchor node is to send out beacon signal to help the moving target nodes for calculating its position. Once target nodes fall within the range of anchor node, listen the beacon for a fixed time period to calculate and collect the RSS information of an anchor node. Euclidian distance between an anchor node and moving target node is calculated. After calculating Euclidian distance, virtual anchors at same distance with different angles are projected by using umbrella projection to localize target node, shown in Fig. 2. In this paper, each node has different transmitting range (due to different battery backups) and DOI used is 0.01. The pseudo codes for umbrella projection and localization using various algorithms is given in Algorithms 1 and 2. Algorithm 1 gives the procedure and applicability of the umbrella projection in the localization process, i.e., for particular target node, distance is calculated between anchor and moving target node (middle or bottom layer) using RSS measures. After that, six virtual anchor nodes are projected at a distance equivalent to calculated distance between anchor and in-range target node with a angle difference of 60 degrees. Then three virtual anchor nodes are selected (Minimum 4 anchor nodes are required for 3D localization) for calculating centroid. After calculating centroid PSO, HPSO, BBO and FA algorithms is applied for optimization. The following steps are followed for finding the positions of moving target nodes:

- M number of mobile target nodes are deployed randomly at the middle and bottom layer of the 3D sensing field of highly chaotic cubic structure with three layer environment and single anchor node is deployed at the top layer of the sensing field. Anchor and target nodes have different transmission ranges due to their different battery backups.
- Each moving target node falls under the range of anchor is considered as localizable. A list is maintained by each localizable moving target node that contained distance information between respective moving target and anchor node. Further, three virtual anchor nodes in surrounding of the target node are projected with umbrella projection to localize itself (as minimum four anchor nodes are required to localize to find the 3D position of the target node), shown in Fig. 3
- By considering the Radio Irregularity Model (RIM) property and heterogeneity property, distance is calculated between anchor (along with virtual anchor nodes) and target nodes by using $\hat{d}_i = d_i - (D_p + F)$, in which d_i is the actual distance given by (8), D_p is the DOI adjusted path loss and F is fading due to anisotropy property. By using the virtual anchor nodes, problem of LoS is

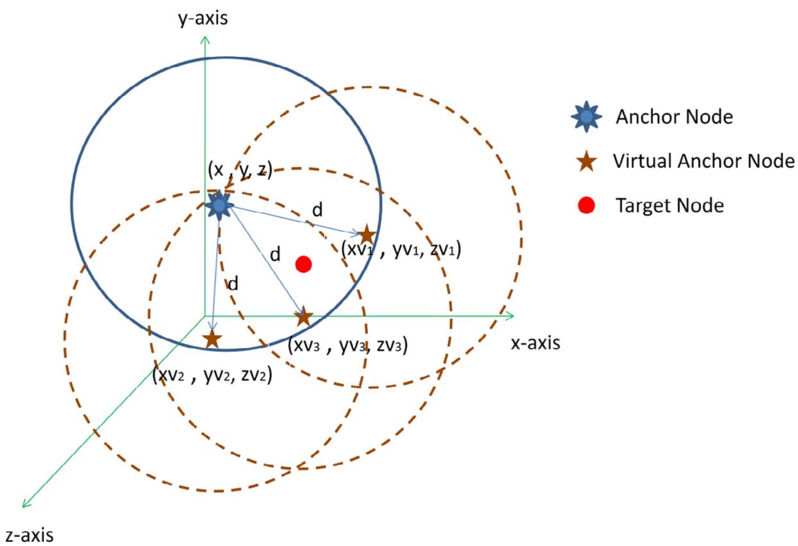

Fig. 3. Virtual anchor node projected in surrounding of anchor node.

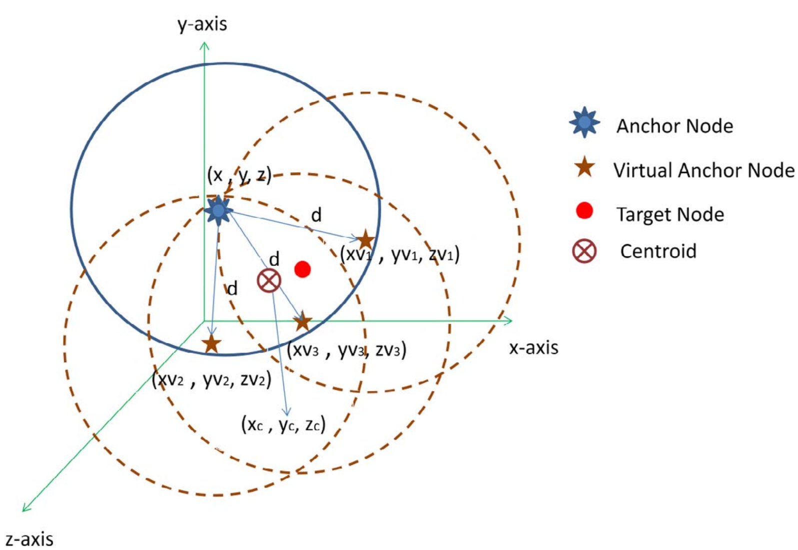

Fig. 4. Estimated centroid by using anchor and virtual anchor nodes.

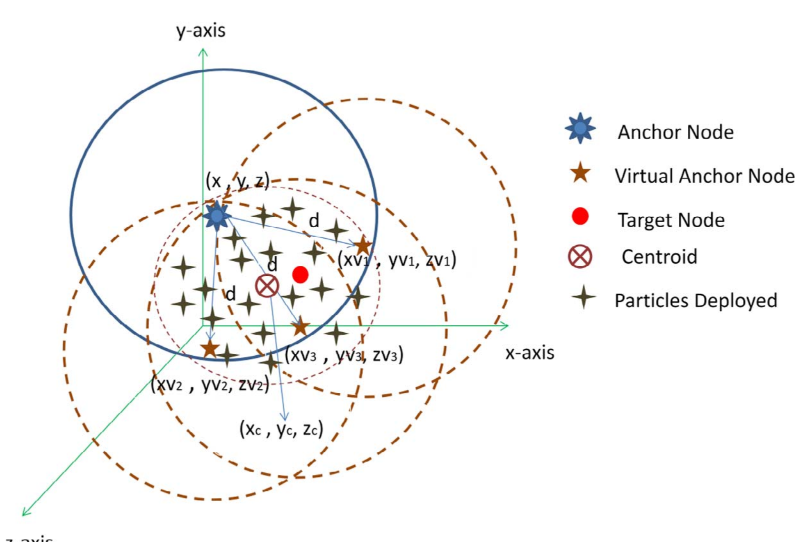

Fig. 5. PSO implementation around the centroid.

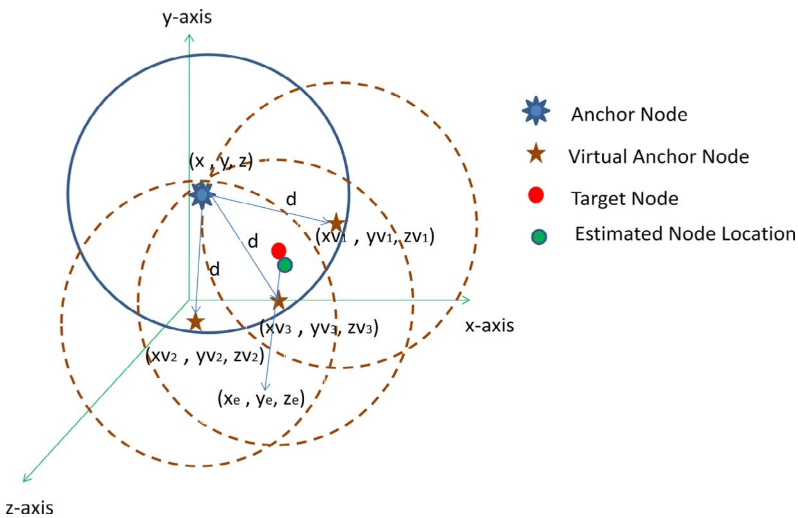

Fig. 6. Estimated target by implementing algorithm.

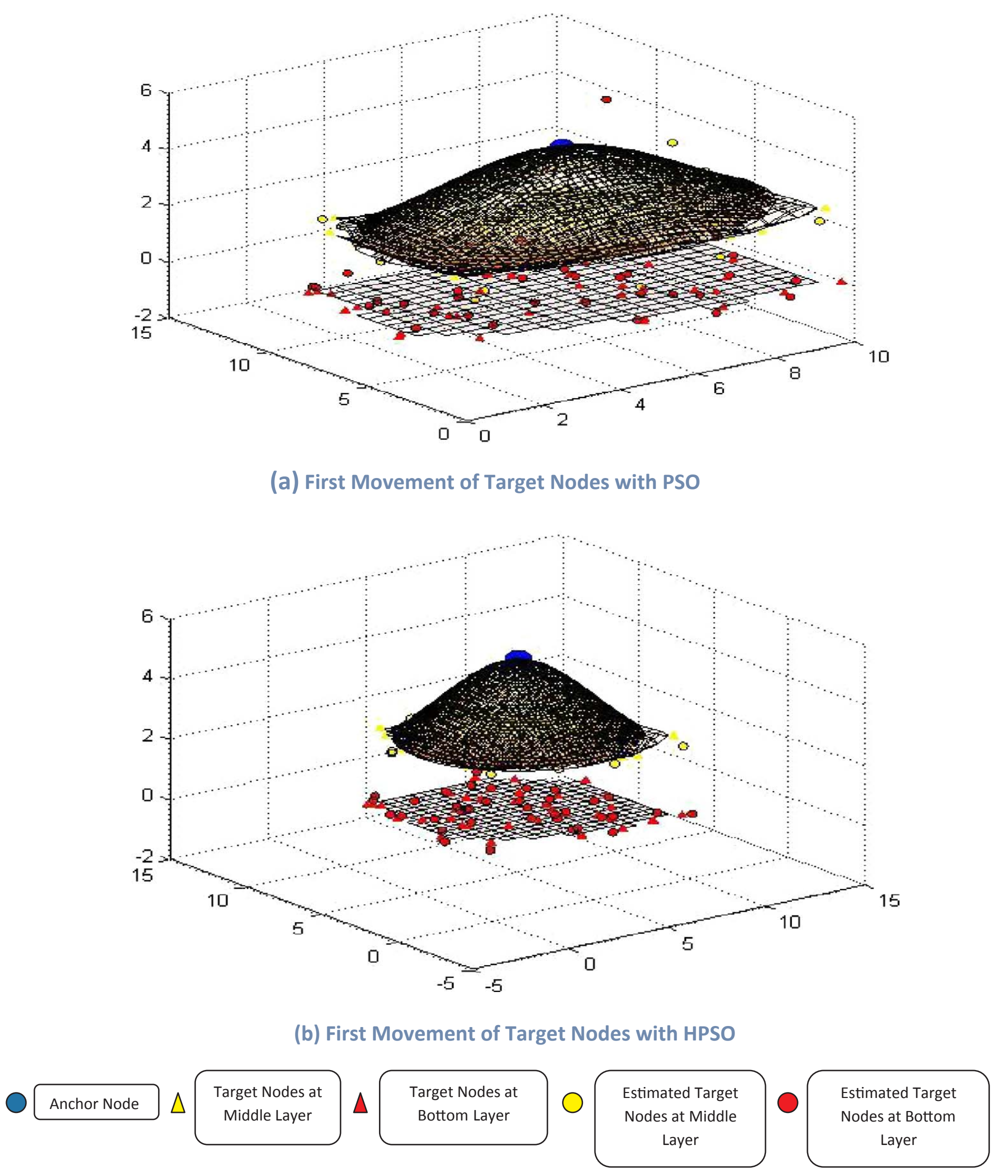

Fig. 7. First movement of target nodes with PSO and HPSO.

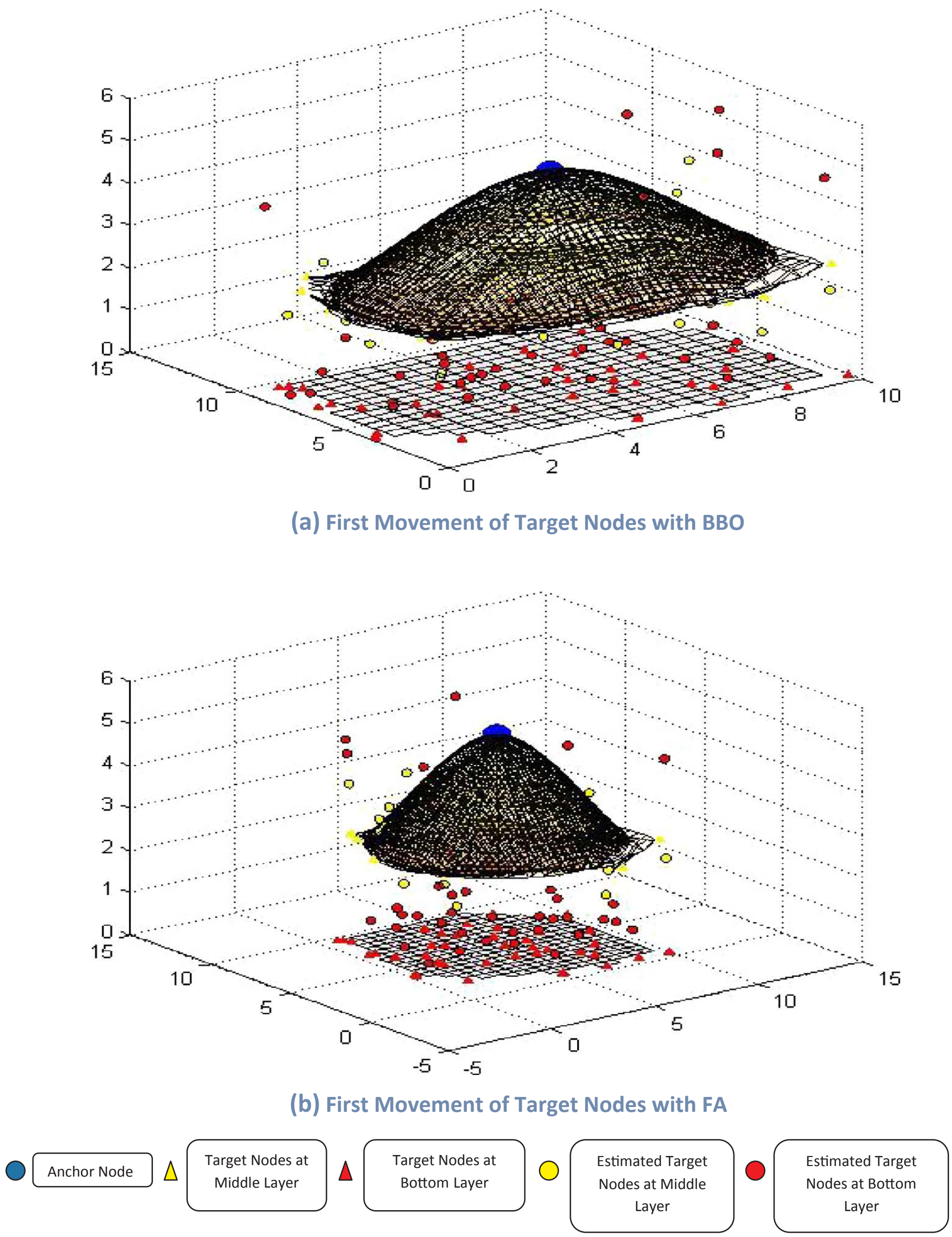

Fig. 8. First movement of target nodes with BBO and FA.

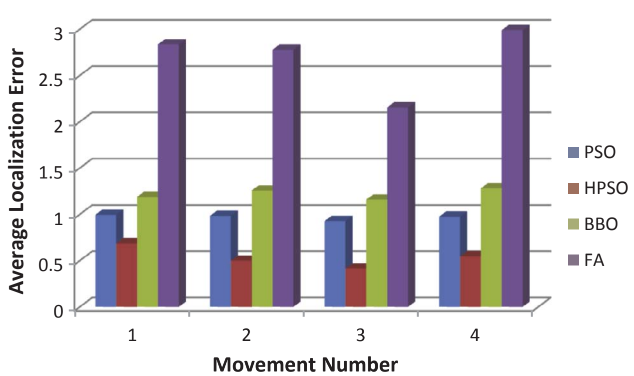

Fig. 9. Average distance between actual and estimated node with different algorithms.

reduced.

$$d_i = \sqrt{(x_t - x)^2 + (y_t - y)^2 + (z_t - z)^2} \tag{8}$$

whereas (x_t,y_t,z_t) is the location of the target node and (x,y,z) is the location of the anchor node [32].

- The centroid coordinates (x_c,y_c,z_c) by considering both anchor and virtual anchor nodes are calculated by (9) where (xv_1,yv_1,zv_1), (xv_2,yv_2,zv_2) and (xv_3,yv_3,zv_3) are coordinates of virtual anchor nodes, shown in Fig. 4

$$(x_c,y_c,z_c) = \left(\frac{x + xv_1 + xv_2 + xv_3}{4}, \frac{y + yv_1 + yv_2 + yv_3}{4}, \frac{z + zv_1 + zv_2 + zv_3}{4}\right) \tag{9}$$

- After getting centroid, particles (population) are randomly deployed

Table 1
Summary of simulation results comparison for PSO, HPSO, BBO and Firefly algorithms for first four counts.

Algorithm	Movement number	Maximum localization error (L Units)	Minimum localization error (L Units)	Average localization error (L units)	Number of target nodes localized
PSO	1	3.9358	0.0554	0.9958	80
	2	5.3379	0.0831	0.9839	80
	3	5.0108	0.0800	0.9267	80
	4	5.1655	0.0367	0.9757	80
HPSO	1	3.2204	0.1144	0.6850	80
	2	5.0034	0.0547	0.4999	80
	3	4.8079	0.0876	0.4139	80
	4	5.1366	0.0320	0.5472	80
BBO	1	5.8904	0.1822	1.1892	80
	2	5.3500	0.3318	1.2560	80
	3	5.5989	0.1822	1.1585	80
	4	5.6348	0.1528	1.2818	80
Firefly Algorithm	1	5.6804	1.2332	2.8355	80
	2	5.8663	1.1178	2.7786	80
	3	5.0122	1.3227	2.1543	80
	4	5.7677	1.4346	2.9905	80

Table 2
Summary of simulation results comparison for PSO, HPSO, BBO and Firefly algorithms for static scenario.

Algorithm	Maximum localization error	Minimum localization error	Average localization error
PSO	2.6886	0.0225	0.6524
HPSO	0.4942	0.0230	0.2162
BBO	1.9910	0.1607	0.8659
FA	2.3514	0.8774	1.5974

around the centroid node within a range of $1unit$, shown in Fig. 5. CI based algorithm is run by each moving target node to localize itself by finding its coordinates (x_s,y_s,z_s). The objective function (mean of square of error between actual and estimated distances of computed node coordinates and the actual node coordinates), given by (10) is minimized. Here, (x_e,y_e,z_e) is an estimate of the target-node location, (x_i,y_i,z_i) is the location of beacon node i (having anchor and virtual anchor nodes), and $M \geqslant 4$ is the number of beacons in the neighborhood of the target node [33].

$$f(x_s,y_s,z_s) = \frac{1}{M}\sum \sqrt{(x_e-x_i)^2+(y_e-y_i)^2+(z_e-z_i)^2}-\hat{d}_i \tag{10}$$

Similarly HPSO, BBO and FA are run by each moving target node to localize itself.

- Each algorithm evolve the optimum location of target nodes as shown in Fig. 6, i.e., (x_t,y_t,z_t) by minimizing the error function.
- localization error is computed by using mean square of distances of computed node coordinates (x_e,y_e,z_e) and the actual node coordinates (x_t,y_t,z_t), given in (11). Where N_L is the number of target node localized.

$$E_t = \frac{1}{N_L}\sum \sqrt{(x_e-x_t)^2+(y_e-y_t)^2+(z_e-z_t)^2} \tag{11}$$

5. Simulation results and discussion

In this paper, a novel idea of virtual anchor nodes have been proposed with umbrella projection around moving target nodes to evaluate the 3D positions in an anisotropic environment using application of Particle Swarm Optimization (PSO), H-Best Particle Swarm Optimization (HPSO), Biogeography Based Optimization (BBO) and Firefly Algorithm (FA). The WSN 3D localization simulations in mobile scenario are conducted in MATLAB environment. These simulations have been taken on the PC having Intel Core i3 2.30 GHz processor and 2 GB of RAM. Only single anchor node is used as a reference (anchor) node to localize 80 moving target nodes in the 3D network. In this paper, authors considered a highly chaotic cubic structure with three layer environment and heterogeneous properties of the nodes. Target nodes are randomly deployed over the second and third layers that are moving in the random fashion. Once a moving target node falls under the range of deployed anchor node, three virtual anchor nodes (minimum four anchor nodes are required for 3D static position) in surrounding (anchor and respective moving target node) are projected with umbrella projection to find the 3D position.

Our strategic settings are specific to all respective application of PSO, HPSO, BBO and FA algorithms are given below.

5.1. Parameters taken for PSO, HPSO, BBO and FA

In the proposed framework, each mobile target node that can be localized run PSO, HPSO, BBO and Firefly algorithms to localize itself. The Anchor position taken for all algorithms is [5,5,5] and the target positions are taken randomly at middle and bottom layers. The parameters for mobile node localization by PSO and HPSO algorithms are:

1. Population Size = 20.
2. Max No. of Iterations = 100.
3. Inertia weight (w) = 0.729.
4. Number of target nodes at bottom layer = Number of target nodes at middle layer = 40.
5. Cognitive learning parameter (c_1), social learning parameter (c_2) and neighborhood learning parameter (c_3) = 1.494.
6. Random number, i.e., r_1, r_2, and r_3 = [0,1].
7. Noise variance = 0.1.
8. DOI = 0.01.

Similarly strategy parameters for BBO algorithm taken for mobile node localization are:

1. Population Size = 20.
2. Max No. of Iterations = 100.
3. Probability of mutation of particle weight = 0.05.
4. Number of target nodes at bottom layer = Number of target nodes at middle layer = 40.
5. Maximum rate of Emigration = 1.
6. Maximum rate of Immigration = 1.

The design parameters of firefly localization algorithm for mobility based scenario is given as:

1. Population Size = 20.
2. Max No. of Iterations = 100.
3. Number of Fireflies = 20.
4. Number of target nodes at bottom layer = Number of target nodes at middle layer = 40.
5. Randomizing Coefficient, $\alpha = 0.2$.
6. Absorption Coefficient, $\gamma = 0.96$.

Applications of PSO, HPSO, BBO and FA based localization algorithms are evaluated for mobility based scenario, as detailed in the above section. The initial deployment of target nodes is random at bottom and middle layer. Anchor node is deployed at the top layer of the sensing field. The target nodes are randomly moving and the anchor node is static. The simulation is done in the MATLAB software. Average of total localization error is considered as fitness function. The algorithms used for localization are stochastic; so, there will be no identical solution for same deployment. Spatial results of proposed localizing algorithms using application of PSO, HPSO, BBO and FA algorithms are given in Figs. 7 and 8 respectively. It is clearly seen in these figures that anchor node makes umbrella projection of virtual anchors (minimum three virtual anchors) in surrounding of anchor node and respective target node. By considering this virtual projection, the problem of Line of Sight (LOS) is minimized. Further it is observed that the HPSO and PSO based algorithms have better accuracy and fast convergence whereas BBO and FA algorithms are less accurate and slow convergence.

In case of static environment, the anchor node range is taken less and the nodes localized through that single anchor is considered as pseudo anchor nodes. The rest of un-localized target nodes are localized by these pseudo and initial anchor nodes. In static scenario, the convergence rate is slow due to consideration of pseudo anchor nodes and the algorithm runs more than one time to localize all nodes. In case of moving environment, the range of anchor node is taken more so that maximum number of target node can be localized in a single shot.

The initial deployment of all targets and anchor nodes are same for all algorithms. The average location error, i.e., mean of the distance between actual and estimated target nodes is shown in Fig. 9 for all proposed methods. To evaluate the performance of the proposed localization algorithms, following performance indices are considered and results for mobility based environment are summarized in Table 1 and for static environment, results are summarized in Table 2. The convergence time in mobility based scenario for PSO and HPSO is very less i.e., 0.4417 and 0.3722 s (For Localizing all 80 Target nodes) respectively and the convergence time for BBO is approximately 1 s. For FA algorithm, the convergence time is maximum (about 10 times the PSO algorithm). There is an impact of flip ambiguity in 3-dimensional node localization, but in this paper only single anchor node has been used for localization and the algorithms used has iterative process. Considering the above, the issue of flip ambiguity is not likely to be much severe and same can be evaluated in a separate study.

6. Conclusion and future scope

In this paper, range-based node position finding techniques using application of PSO, HPSO, BBO and FA algorithm for distributed and anisotropic WSNs are proposed using single anchor node. Virtual anchor nodes are projected by using umbrella based projection from the anchor node. Once a moving target node falls under the range of deployed anchor node, three virtual anchor nodes (minimum four anchor nodes are required for 3D position) in surrounding (anchor and respective moving target node) are used to find the 3D position. The proposed algorithms can be used for the applications like underwater localization, logistics, localization of an event in a remote and hilly area, coal mine workers tracking and various industrial applications.

Proposed algorithms also likely to conserve energy in an anisotropic network as the localization is being done by single anchor node only (no need of physically presence of other three anchor nodes) but the energy issue does not fall in the scope of this work and same can be evaluated in a separate study.

The proposed HPSO and PSO based algorithms have better performance as compared to BBO and FA algorithms. In BBO based algorithm, convergence rate is slow. Further the proposed algorithms may be implemented for centralized localization and range free multi-hop localization for mobile targets or mobile anchors. To achieve more accuracy, a hybrid algorithm can be proposed.

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