WSN Localization by using GWO and Cuckoo Search Algorithm (CS)

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Abstract: In WSN field, accurate location of sensor nodes is highly required and some of the sensing operations require the location of target node. These are used usually to sense the temperature, moisture etc and fault tolerant. We used a hybrid heuristic optimization method to accurately locate the host sensor node which is the hybrid of Grey wolf optimization algorithm (GWO) and cuckoo search optimization (CS). Both algorithms are combined to use the advantages of both and results are compared with GWO optimization only. The hybrid function is also tested over few unconstrained linear and non linear benchmark functions and GWO-CS is the winner in terms of minimum fitness value in each function. The work is evaluated on the basis of mean localization error, number of localized nodes and computation time in each case. The nodes localization is a complex problem and backed by several constraints. This needs the division of nodes into anchor, reference and unknown nodes. Anchor nodes are equipped with GPS to know their location exactly. These help to find out other nodes' positions. In our test cases which differ by geographical area in which nodes are placed, we found a optimal area of 100 m^2 for the maximum number of localized nodes and minimum localization error. Each test case is tested with different number of anchor nodes and it has been found that in 100 m^2 area, 80 anchor nodes give maximum number of localized nodes. By our proposed hybrid optimization algorithm, an improvement of 13.8% is achieved over GWO localized nodes.

Keywords- WSN, GWO, Cuckoo search algorithm etc.

I. INTRODUCTION

Location of sensor node is very crucial in a sensor network since many application such as monitoring forests and/or fields ,where a large amount of sensor nodes are placed. An efficient localization algorithm can determine the accurate position coordinates of devices or nodes using the information available from sensor nodes. In addition ,location based routing protocol can save and utilize significant amount of energy by removing the need for route finding and improve the location for application. In wireless sensor networks , the problem of determining the location of unlocalized sensor nodes is referred to as localization. Localization can be achieved using any of these methods:

- Anchor-free v/s Anchor based
- Centralized v/s distributed
- Range-free v/s Range based

Challenges faced during Localization

i. Because of the arbitrary deployment of sensor nodes ,a uniform distribution of nodes can't generally be achieved, which may create a situation where few areas could not have any sensor node.

ii. Uneven power usage among sensor nodes results in some regions without usefulness of sensing and communication.

iii. Wireless sensor networks are liable to be arbitrarily deployed in out of reach terrains and environments such as war zone and clash zone , as well as inhabitable regions etc .Physical deterrents , for example ,mountains or buildings will naturally exist in numerous networks.

iv. Sensor networks are typically quite resource-starved. Sensor nodes are normally battery controlled. Communication, processing and sensing movements will diminish the lifespan of the node. So, they must work to reduce the power cost, equipment expense and deployment cost.

II. GREY-WOLF OPTIMIZATION(GWO)

Grey wolf belongs to Canidae own family Grey wolves ordinarily favor to stay in a percent. The group length is 5–12 on common of unique hobby is they have a very strict social dominant hierarchy as proven in Fig. 1. The leaders are a male and a lady, known as alphas. The alpha is in general accountable for making selections about hunting, sleeping location, time to wake, and so on. The alpha's choices are dictated to the p.c.. Grey wolves are taken into consideration as apex a predator that means that they are on the pinnacle of the food chain. Grey wolves ordinarily favor to stay in a percent. The second degree within the hierarchy of gray wolves is beta. The betas are subordinate wolves that assist the alpha in choice-making or different percent sports.

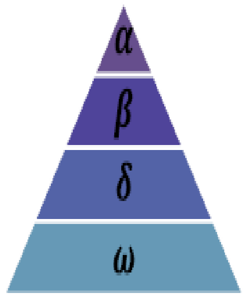
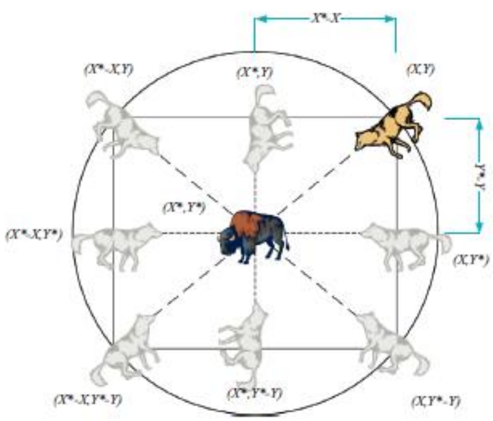


Fig .1. Hierarchy of grey wolf (dominance decreases from top down). [13]

In gatherings, the complete percent recognizes the alpha by preserving their tails down. The alpha wolf is also called the dominant wolf in view that his/her orders have to be accompanied with the aid of the %. The alpha wolves are most effective allowed to mate within the %. Interestingly, the alpha is not always the most powerful member of the p.C.But the fine in terms of handling the p.c. This shows that the corporation and subject of a percent is a great deal extra crucial than its electricity.

Grey wolves have the capability to apprehend the region of prey and encircle them. The hunt is generally guided through the alpha. The beta and delta can also participate in looking once in a while. However in an abstract seek space we don't have any concept approximately the place of the top-quality (prey).



(a)

Fig. 2. 2D and 3D position vectors and their possible next locations. [13]

III. CUCKOO SEARCH ALGORITHM

When cuckoo grows up and ready to lay eggs then they look for bets habitat. The groups of cuckoo start looking for it. To divide them into groups, k-means clustering algorithm is used. 3-5 cuckoos in a group are sufficient from simulation point of views. Each group calculates their mean value of profit and maximum value of profit in these groups is the goal and best habitat to move as shown in figure 3.

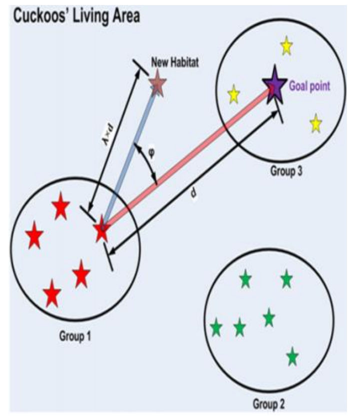


Figure 3: Immigration of sample cuckoo towards goal [14]

On finding the best location, cuckoo don't move right towards the goal but they move in steps as in figure 3.7. Each cuckoo move only λ distance and deviates by ω radian to continue search the nearby environment. Once the cuckoo reaches to optimal position, it starts laying eggs and that is optimal solution of any application where cuckoo optimization is working. Those other cuckoos which trapped in other habitats, their eggs get killed by host birds and called worst habitat. The cuckoo optimization algorithm in the best habitat converges when 95% of eggs get successfully laid.

IV. PROPOSED WORK

GWO operates on the basis of hierarchy in the group. Once all wolves are initialized with some random feed then fitness function is calculated for each wolf. In a group 10-20 wolves are considered. Out of them the one with minimum fitness function (as GWO works to reduce the distance between prey and wolf and optimal position is the prey position whereas CS works for maximization of profit) is considered as leader of the group and α_wolf, followed by two more wolf with corresponding decreasing fitness function as β_wolf and γ_wolf . The mean of these positions is considered as optimal position of wolf in that iteration.

$$GWO\ optimal\ position = \frac{\alpha_{wolf} + \beta_{wolf} + \gamma_{wolf}}{3} \qquad \ldots..(1)$$

Top three wolf positions are updated by equations and new position is the mean of these three. In GWO, to move towards the prey, the distance between prey and golf is minimized and changed over time. The step size by which wolf moves is randomly weighted by a constant which leads to fall it into local optima. This problem is solved by cuckoo search algorithm which update the current position based on the best position so far. CS optimality is more relied on other habitat groups rather than only time. To make it hybrid we updated the best three locations of wolves in the group by CS method which update it by a step of λ with angle ω. The step size is updated as:

stepsize=w*step.*(s-best); ....2)

where 's' is the position of alpha_wolf, beta_wolf and gamma_golf

'step' is the previous step size of cuckoo movement

'stepsize' is the updated step size

'w' is the weighting factor = 0.001

The position of cuckoo is now updated as:

$$s = s + stepsize \times \omega \qquad \ldots..3)$$

whereω is the deviation of cuckoo and a random quantity.

Using equation 3 the $\alpha_{wolf}, \beta_{wolf}, \gamma_{wolf}$ are updated to new positions and handle will get back to GWO form CS. Now GWO takes mean of all three best positions again and tradeoff the local optima error in this hybrid. We tested this hybrid GWO-CS function on benchmark functions too and compared with GWO algorithm as can be checked in table .1. We took benchmark function reference from GWO paper [13]. We used few random functions from different benchmark function categories. It has been observed that hybrid approach of GWO-CS is performing better than GWO only and removes the local optima issue in previous work. Every objective function's 3D surface view is also shown in table along with the convergence curve. The lower the curve better is the algorithm as parameter space 3D view is pointing/converging towards a minima point.

4.1: Node localization using GWO-CS

To location the location of unknown nodes in WSN, we are fine tuning the location considered by the RSSI method. All nodes are categorized into three categories: anchor nodes, reference nodes and unlocalized nodes. Anchor nodes are those nodes whose position is known to base station, those unlocalised nodes whose positions are determined by the algorithm are reference nodes and can take part in locating the other un-localised nodes. Hybrid method finds the location of sensor nodes optimally and compare the distance with the actual one. The minimum is the error, better is the position. The GWO-CS and node localisation are two isolated system but their dependency can be depicted as in figure 4.1. These collectively forms a feedback loop. The module of GWO-CS gets the relative error of distance of nodes in the input and gives the updated nodes' positions to the WSN module.

There are two tuning variables for each unlocalised node in the area which represents the x and y co-ordinates of the node. These tuning variables are the positions of wolves and updated by hybrid optimisation to find a node with minimal distance from the actual location. The error must be minimum.

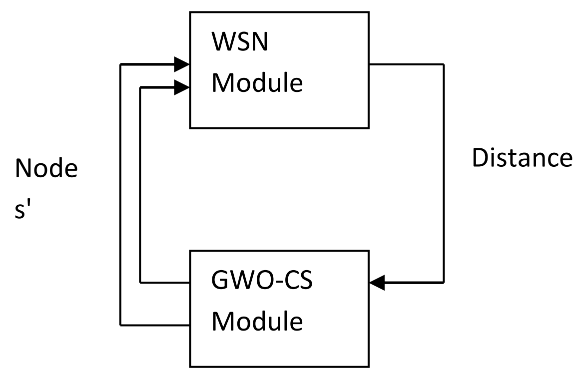


Figure 4.: Relation between node localization and GWO-CS optimization

The optimisation process is the iterative process and in each iteration the each wolf position will be updated and sent to WSN module in figure 4 which calculates the distance error.

4.2 WSN Module

There is constraint in the WSN module, only that node can be localised which is in range of at least three anchor nodes. If node is not in range of three anchor nodes, either that is dropped or a new position is assigned to that node. The distance of that un-localised nodes is calculated from all anchor nodes in vicinity and relative difference of sum of measured distance and sum of calculated distance (RSSI method) is observed which is passed back to optimization module. If any un-localised node is localised then it acts as reference node and helps the anchor nodes to find out the other nodes' position as anchor nodes.

Steps for Unknown Node Localisation

Step1. randomly place the nodes in an area of $100 \times 100\ m^2$

Step2. Fix the few sensor nodes as anchor nodes whose locations are known and rest are to be localized.

Step3. Measure the unknown node's locations using RSSI method. These locations will be used to compare the calculated distance by hybrid optimization algorithm.

Step4. start a loop for each node and call the optimization module. Inside this module, initiate the wolf position randomly within the WSN geographical area which is [1,100].

Step5. for each wolf, optimisation module (objective function) is called which checks if that node is in the vicinity of at least three anchor nodes. if yes, then distance from those anchor nodes is calculated and compared with the distance of corresponding measured node (step 3) with anchor nodes.

Step6. Relative error is calculated and sum of Relative error is passed back to GWO-CS optimization. This step is repeated for every grey wolf in the group.

Step7. Top three best wolves are selected for which error comes out to be minimum in present iteration and these wolf's position are updated by cuckoo search optimization by equation:

$$s = s + stepsize \times \omega$$

notations are given in section 4.1. The step size is calculated as in equation 4.2.

Step8. Updated positions for three best wolves are used to calculate the overall best position for present iteration and step5 is called again to calculate the relative error.

Step9. This process continues till whole iterations for each nodes are not finished.

Step10. results are evaluated on the basis of minimum localization error, number of localized nodes and computation time.

Step11. A comparison is done with the GWO results for all these three parameters.

V. RESULTS & DISCUSSION

This research work is focused on nodes localization in WSN network for emergency fields like in army or in natural calamities etc. We have proposed a novel optimization algorithm to know the location of sensor nodes n the field and the whole process is developed and simulated using MATLAB. MATLAB provides a wide tool variety which helps and ease the work to implement the main algorithm rather than wasting the time to write every basic part. We developed the module for GWO-CS optimization and its objective function mainly along with WSN architecture. Test cases are defined for various geographical region like 50 square meter, 100 square meter and 200 square meter for different number of anchor nodes out of total 200 nodes. For each case the program evaluates the results for [20,30,40,50,60,70,80,90,100] anchor nodes and rest are unknown nodes. For comparison both GWO and GWO-CS are evaluated on each parameter. We considered 10 wolves in a group with 10 iterations. The table .1 include the details of WSN deployment and optimization.

Table 1: WSN node localization parameters

Total sensor nodes	200
Geographical area	50 m^2, 100 m^2, 200 m^2
Sensor node Transmission range	20 meter
Number of anchor nodes	20,30,40,50,60,70,80,90,100
Maximum number of iterations	10
Optimization algorithm	GWO-CS, GWO

Test case1 : 50 square meter WSN area

We run the simulation for 200 nodes considering the various number of anchor nodes. 200 sensors nodes are deployed randomly in the 50 square meter area and tested for 10 anchor nodes initially followed by 20,30.. 100 anchor nodes. Results are evaluated first by GWO-CS optimization algorithm and for the same number of anchor nodes, GWO evaluates the results. The convergence curve for the proposed solution is shown in figure 5. This curve is the comparison of mean of relative error vs number of iterations in GWO-CS and GWO. We used same setting for both optimizations.

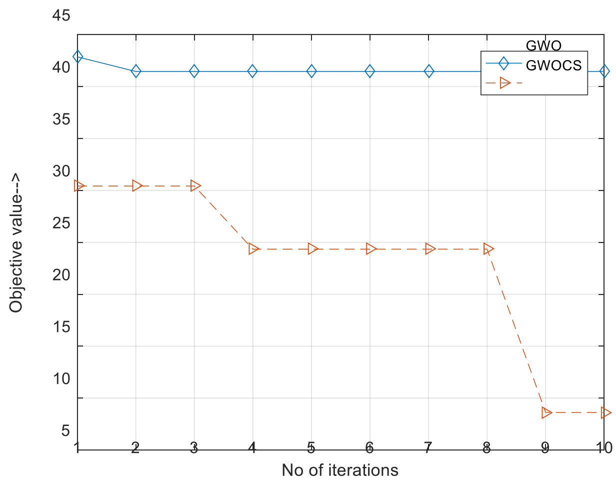


Figure 5.: Convergence curve for GWO-CS and GWO for 50 m^2 WSN area

The convergence curve must be decreasing with number of iterations and must converge as soon as possible. Since it is plotting the relative error, so most least value would be considered and is clear from figure that GWO is minimized and settled at 42 approximately whereas in hybrid method it is at approximate 8. Since it is relative error, it has no unit. This convergence curve is for the case in which 100 anchor nodes are considered and it shows that GWO-CS convergence is better than GWO.

Total nodes deployed in the region is shown in figure 6 and 7 for both optimization methods. 200 nodes are deployed, out of which 100 anchor nodes are shown in green square box marker in both figures. We used the same anchor nodes' positions in both optimization cases so that an exact comparison can be done.

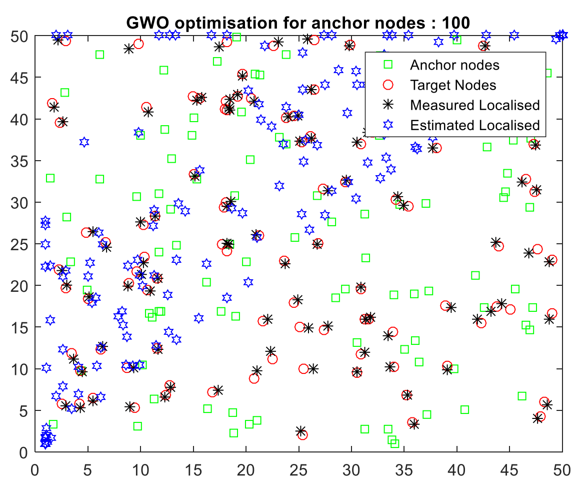


Figure 6: Estimated nodes position by GWO optimization in the region

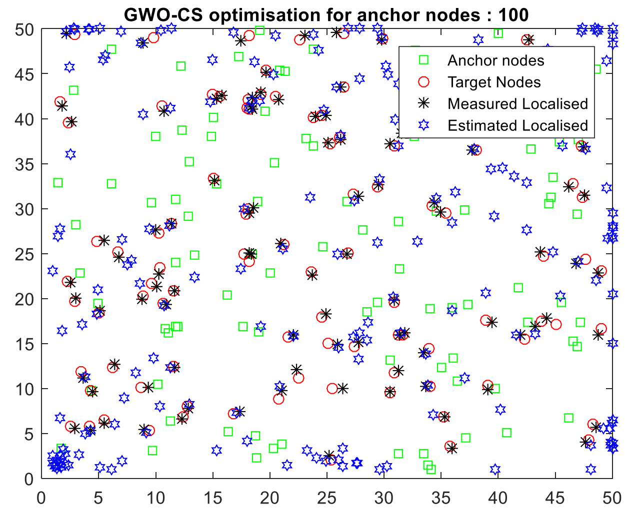


Figure 7: Estimated nodes position by GWO-CS optimization in the region

The mean localization error for hybrid optimization algorithm is less than the GWO only and in correlation with that the number of localized nodes also follows the same pattern. For the case in 50 square meter area, the number of localized nodes are more in case of less number of anchor nodes as compared to GWO but as the anchor nodes number increases, GWO also perform as good as hybrid optimization whereas computation time for GWOCS is more than GWO for each anchor nodes case.

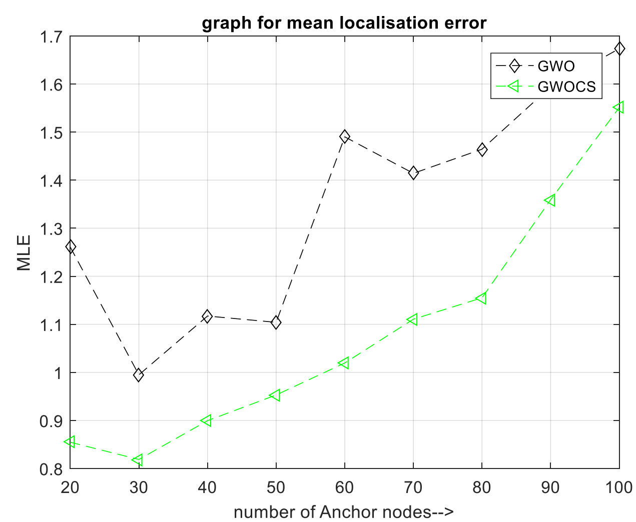


Figure 8: Comparison of computation time vs number of anchor nodes

Test case2 :100 square meter WSN area

This case is tested with 100 square meter WSN area with other stats same as previous case. The convergence curve for this case is shown in figure 9. The GWO-CS is converging at less scale than GWO which proves the evaluation results of proposed hybrid method will be better than GWO. More number of nodes will be localized in GWO-CS method. The table for the parameters is shown in table. It is clear that mean localization error for hybrid algorithm is lesser than only GWO optimization for every case of number of anchor nodes. The error is almost decreasing with increase in number of anchor nodes as with more anchor nodes in area, an unlocalized node can be in neighborhood of many anchor nodes and more accurate location can be determined in those cases. Similar convention applies on number of localized nodes parameter. If the localization error will be less, more will be localized nodes. The computation time is calculated using tic-toc command of MATLAB. The time must be reducing with the increase in number of anchor nodes but there is also possibility that in those anchor nodes' transmission range, several possible locations of that unknown nodes may lie. The computation time also depends upon that. If only few possible positions will lie then computation time will be lesser. The graphs for Mean localization error, number of localized nodes and computation time for 100 square meter area is shown in figures 10.

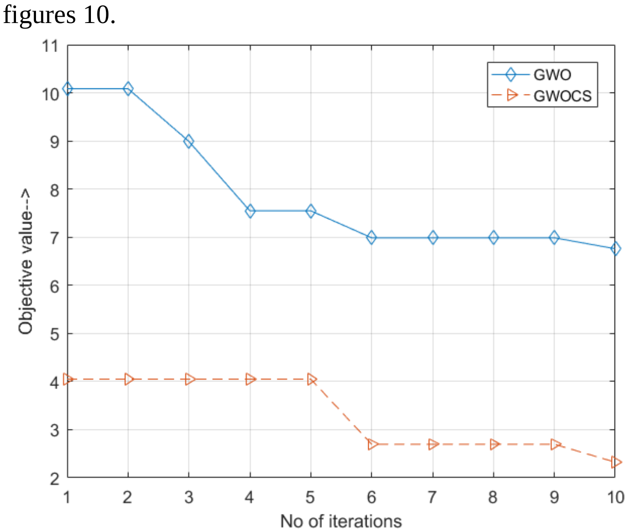


Figure 9: Convergence curve for 100 m^2 area for GWO-CS and GWO

On calculating and analyzing the proposed method in three different area where sensor nodes can be placed, we compared our hybrid optimization method results to determine in which case it gave best result. A bar chart for mean localization error is shown in figure 5.9 based on the collective results of three cases and figure 5.10 shows the number of localized nodes. It is analyzed that the mean localization error is more in large geographical WSN area and so the number of localized nodes is higher. Though the localization error curve is only for these nodes whose locations has been identified and the error graph indicates the deviation of their position from measured one. In small region both parameters are performing better than other.
In small region like 50 square meter, due to highest node's density the number of identified nodes is decreasing with the increase in number of anchor nodes due to packet loss in small region with high density of anchor nodes. As anchor nodes broadcast asynchronously in the network and waiting time for these messages increases due to many broadcasting source, whereas in large region it is not the issue and it follows the increment with the anchor nodes.

VI. CONCLUSION

Our work is based on WSN nodes localization which is required for those cases where sensor data collection is necessary but manual installation of sensor nodes is not trivial. So random position of nodes from some other mean is done with few nodes in that communication area with known positions due to GPS installed. Other node's positions is to be determined to bring the network in alive. We adopted a hybrid heuristic optimization algorithm for this purpose considering the constraint of three anchor nodes in the transmission range. This algorithm is based on the local behavior of Grey Wolf Optimization (GWO) algorithm and global behavior of Cuckoo Search Algorithm (CS). We combined them to use the strength of GWO and CS. The hybrid function is also tested ion some benchmark functions on which GWO was tested earlier by the author and it surpassed their results. For each kind of benchmark functions whether that is unimodel or multi model, hybrid GEO-CS method performed better and converge at better scale then GWO only.

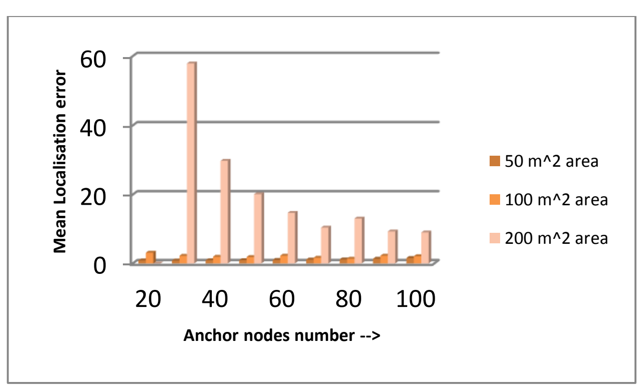


Figure 10: Comparative analysis of proposed solution in node localization in three different scenarios

We used this hybrid method in our problem of node localization which was previously solved using GWO optimization by calculating the relative error between the calculated position and measured position for each node. Results are analyzed for mean localization error and number of localization nodes mainly for three different geographical WSN areas. it has been analyzed that the proposed hybrid method localized more nodes than GWO only in each scenario. A behavior is analyzed that if geographical area is smaller and number of anchor nodes is more than also less unknown nodes are localized due to more waiting time. For very large area less number of nodes are localized as in case with 200 square meter region. So optimally the 100 square meter area is chosen for more number of localized nodes. The anchor nodes' number also affects. As in analysis in

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