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Secure Localization in UWSN using Combined Approach of PSO and GD Methods

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Abstract: ***Particle swarm Optimization (PSO) is a well known global optimization algorithm best suited for solving complex real world problems. But it has a problem of getting stuck in local minima in certain cases. To mitigate this problem, some researchers have applied modification by hybridizing it with best suited local optimization algorithms with it. In this paper, we have put forward our try to combine Gradient-Descent (GD) optimization algorithm with Particle Swarm Optimization (PSO) for localization of sensor nodes in UWSN. Algorithm works in two stages. In the first stage, GD approach is used to identify the local best particle in local neighborhood. In order to enforce the security during localization, GD is combined with Maximum Likelihood (ML) method to identify the suspicious nodes in the swarm. Second stage of the work continues with finding global best solution using PSO. The experiments have shown that combined approach of GD and PSO have better performance over current approaches in terms of security and accuracy.***

Index Terms: ***gradient-descent, maximum-likelihood, mitigate, neighborhood, optimization***

I. INTRODUCTION

Every Wireless Sensor Network (WSN) based application works effectively based on the location information of the connected sensors in the deployed network. It is important to make sure that the position estimate of each sensor is accurate and secure. Hence the localization algorithms which are devised for the purpose have to integrate mechanisms to identify the suspicious nodes and isolate them from participating in the localization process. Broad number of researches have been done on localization where as less focus is given on the enforcing security during the process. Hong Li et al [1] have discussed the security and privacy issues in underwater localization. They first reviewed the major localization algorithms proposed for underwater sensor networks and discussed many privacy issues in UWSN localization schemes. P. Ning et.al [2], has proposed attack resistant location estimation in WSNs. To obtain better accuracy, the grid model needed to be more refined which intern resulted in higher memory requirements and computational resources. Ravi Garg, Avinash et.al has proposed An Efficient Gradient Descent Approach for Secure Localization in Resource Constrained Wireless Sensor Networks [3]. The research has shown that Gradient Decent approach gives better results in local neighborhood. He continued in his research and later integrated GD with Maximum likelihood approach to prune the suspicious nodes from localization process. The results were best suited for local environment. This paper presents a secure framework for localization in UWSNs by combining PSO and GD methods. Overall work has been carried out in 2 stages. In the first stage, GD approach is integrated with Maximum Likelihood (ML) to enforce the security during localization there by isolating the suspected malicious nodes from participating in the localization process. In the second stage, the algorithm applies PSO for finding best position of the node in the global search space using diversification. The experiments have shown that the combined approach of GD and PSO has better results than the existing methods in terms of localization accuracy and security.

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II. COMBINED APPROACH OF GD AND ML

Gradient Descent (GD) is a convex function which tweaks its parameters iteratively to minimize a given cost function to its minimum. Mathematically gradient is a partial derivative with respect to its inputs. If we consider the gradient as a vector that contains the direction of steepest step, a cost function is defined to make a move towards the steepest descent in iterative steps. The equation for GD is given in the equation (1)

$$b = a - \gamma \nabla g(a) \qquad (1)$$

where, b denotes the next step to be taken towards the gradient with respect to the current position a. The negative sign indicates the particle movement happens toward the negative gradient and γ represents the step size taken to make an iterative move toward the minima. $\nabla g(a)$ is the gradient. GD selects any random location in the search space and starts moving towards negative gradient taking one step at a time and reaches a point where reduction in cost function will remain same and this state is called the minimal value of the cost function.

The main intuition behind Maximum Likelihood (ML) function is to provide the parameter of statistical distribution which would most likely produce the data similar to the given set. If a swarm has M number of beacon nodes, P_u denotes the target node which undergoes which undergoes localization, P_k denotes the position of the beacon node which estimates the location of the target node and $g(i)$ is the gradient at i^{th} iteration, then, by adopting the ML estimate, the true position of the anchor node would be found by maximizing the above specified probability as given in the Equation (2)

$$P_{k,ML} = arg\ max_p\ P_r(\{d_k\}_{k=1}^{M} | P_u, \{P_k\}_{k=1}^{M}) \qquad (2)$$

The above estimation can be computed by GD. The estimated position of the node P_u in the ith iteration can be computed as in the Equation (3)

$$P_u(i) = P_u(i-1) + \gamma(i) \times \frac{g(i)}{\|g(i)\|} \quad (3)$$

Where, $g(i)$ the sum of the force vectors $\sum_{k=1}^{M} g_k(i)$ and $\gamma(i)$ is the step size in the i^{th} iteration, $\frac{g(i)}{\|g(i)\|}$ is the unit vector in the direction of steepest descent. The value for $g_k(i)$ is computed as in the equation (4)

$$g_k(i) = (\|P_k - P_u(i-1)\| - d_k) \times \frac{P_k - P_u(i-1)}{\|P_k - P_u(i-1)\|} \quad (4)$$

Based on the ML estimation, the anchor nodes which has larger force vectors than the predefined threshold value are considered as suspicious nodes and avoided from participating in localization in the next level. Thus the GD method applies security to the localization at the first stage and the localization process continues with the second stage using PSO to find global best minimal node location. The algorithm for the combined approach for GD and ML is given in Algorithm 1.

Algorithm1

Initialization:

M: Number of beacon nodes

N: number if iterations

P_u : Position of the target node which undergoes localization

P_k: Position of the beacon node which estimates the location of the target node

$g(i)$: Is the gradient in i^{th} iteration

Stage 1: Isolation of malicious beacons from the swarm

Begin

for $i = 1$ to N

for $k = 1$ to M

Compute Gradient

$$g(i) = P_u(i-1) - P_k \times \frac{d_k - \|P_u(i-1) - P_k\|}{\|P_u(i-1) - P_k\|}$$

If $\|g(i)\| < theshold\ OR\ Stage == 2$ then

Switch to Stage 2

Stage 2: finding the local best

Let L be the set of non- malicious nodes

Compute gradient for all the beacons in L

$$g(i) = \sum_{k \in L} g_k$$

Update

$$P(i) = P(i-1) + \gamma(i) \times \frac{g(i)}{\|g(i)\|}$$

End

III. PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) is an intelligent optimization algorithm. It belongs to a class of optimization algorithms called Meta-Heuristics. PSO works based on the paradigm of Swarm Intelligence (SI) and inspired by social behavior of insects, birds and other animals which exhibits the nature of living in swarm. Swarm initially will contain a population of candidate solutions. Each candidate solution is called as a particle in search space for finding the solution. Every particle has its position vector $\vec{x}_i(t) \in X$ specified with respect to time. Particle $\vec{x}_i(t)$ moves towards a vector $\vec{v}_i(t)$. Particles are communicating and learning to find best solution. In addition to the position and velocity, every particle has a memory to store its best experience and denoted by $p_i(t)$. Added to the best experience of the particle, entire swarm will update the best experience $g_i(t)$; this will act as global best and global common experience. Every iteration updates particle's position and velocity.

In successive iteration, particle's position and the velocity will be updated. Based on previous experience, the particle makes a move in parallel to the vector of velocity and somewhat parallel to the vector connecting the x_i connecting to the global best. This position is set as $x_i(t+1)$. Particle x_i updates its new position and velocity as given in the Equation (6) and (7) respectively.

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (6)$$

$$v_i(t+1) = wv(t) + C_1(p_i(t) - x_i(t)) + C_2(g(t) - x_i(t)) \quad (7)$$

Updated velocity of the particle $v_i(t+1)$ has 3 components. The previous velocity of the particle, particle's learning experience and influence of swarm. On constant updates in the model, the update in the velocity of a particle is modified as given in the equation (8)

$$v_{i,j}(t+1) = wv_{i,j}(t) + r_1 C_1\left(p_{i,j}(t) - x_{i,j}(t)\right) + r_2 C_2\left(g_j(t) - x_{i,j}(t)\right) \quad (8)$$

Where, $v_{i,j}(t+1)$ is the particle's velocity at time $(t+1)$, $C_1\ and\ C_2$ are the acceleration components, r_1 and $r_2 \approx U(0,1)$, $r_1 C_1\left(p_{i,j}(t) - x_{i,j}(t)\right) + r_2$ is cognitive component and $r_2 C_2\left(g_j(t) - x_{i,j}(t)\right)$ is the social component which influences the swarm to explore the global region of search space.

IV. COMBINED APPROACH OF PSO AND GD

PSO computes global minima by decreasing the step size of the particle movement to a minimum value. This is achieved by defining a parameter called inertia weight as given in the equation (8). Adding inertia weight to the velocity vector narrows down the search space as search process progresses. Thus reducing the step size to smallest value might make the PSO to come across premature convergence. Hence to avoid premature convergence in the local neighborhood, step size needs to be reduced only in the neighborhood of tentative global minima. To achieve this, we have proposed an effective approach for global localization by combining PSO and Gradient Descent (GD) methods.

Algorithm 2

Begin

Initialization:

Select a random location in search space and for all the particles, initialize:

p_i: Particle's best experience

v_i: Velocity vector

x_i: Current position of the particle

Iteration count: t=1

The best solution: $G = \min_{x_i} f(x_i)$

Set particle index $i = 1$

Compute

Do for each dimension d

$v_{id}(t+1) = v_{id}(t) + r1_d\left(p_{id}(t) - x_{id}(t)\right) + r2_d\left(G_d(t) - x_{id}(\right.$

$x_{id}(t+1) = x_{id}(t) + v_{id}(t)$

Set $i = i + 1$

if $f(x_i) < f(p_i)$ then replace p_i with x_i

if $f(x_i) < f(G)$ then replace G with x_i

if $i < N_p$, go to step *5*

Determine N_G , a derivative based local search (Secure GD algorithm) and store the result in L.

if $f(L) < f(G)$ then $G = L$

Set $t = t + 1$

If $t < t_{max}$ go to step *5*

Else stop

End

Thus a combined approach of GD and PSO is used to apply exploitation with selective node isolation in the first stage and the global exploration for the global minima is found using the PSO algorithm.

V. EXPERIMENTAL RESULTS

A. *Simulation Setup*

The Aquasim simulator of NS-2 is used to implement the combined approach of PSO and GD. The performance is compared with Gradient Descent [6] algorithm based on the parameters localization success ratio, Error rate and Average Energy Consumption. The simulation parameters and settings are summarized in Table 1.

Table 1. Simulation Parameters

Parameter	Value
No. of nodes	200
Test Area	500 X 500 m^2
MAC	Underwater Mac
Simulation time	50 sec
Antenna type	Omni antenna
Channel	Underwater Channel
Channel capacity	2 Mbps
Traffic Source	CBR
Range	100 to 400 m
Packet Size	Bytes
Initial Energy	10000 J
Transmission Power	2.0 W
Receiving Power	0.75 W
Propagation	Underwater Propagation
Traffic Rate	50 Kb
Number of Attackers	1 to 5

B. *Attackers Vs Localization Delay*

Fig.1 shows the overall time taken for localization by both GD and combined approach of PSO and GD methods. As we increase the number of attackers, the delay experienced by both the approaches has been recorded. Gradient Descent increases the delay from 0.006s to 0.01where as, the delay of PSO and GD increases from 0.0040s to .0043s. Hence the delay of PSO and Gradient is 54% of lesser, when compared to GD.

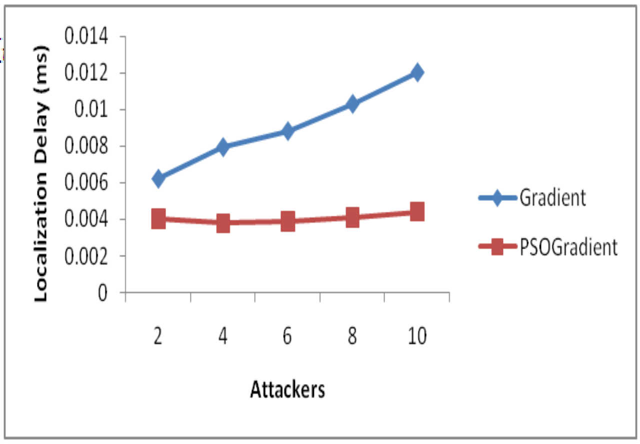

Fig 1: Attackers Vs Localization Delay

C. *Attackers Vs Energy consumption by nodes during localization*

Fig. 2 shows the plot of energy consumption by the nodes during localization process when applied with Gd and Combined approach of PSO and GD in the presence of attacker nodes. Consumption of the node energy varies from 2036.05J to 3260.127J in the case of GD approach, where as in combined approach of PSO and GD, it varies from 1065.11J to 1582.50J. Hence the energy consumption In the case of combined approach of PSO and GD is 50% of lesser when compared to GD.

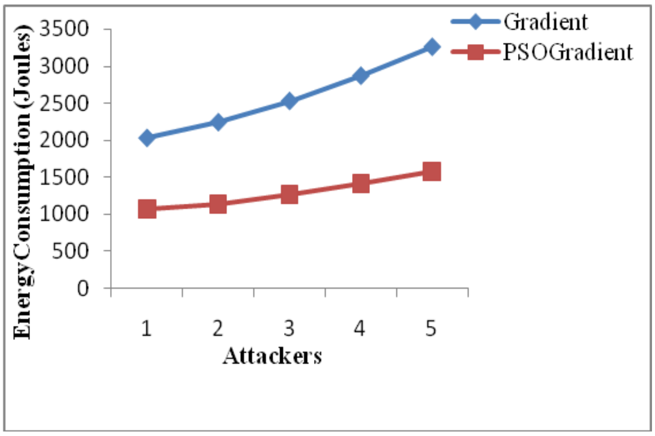

Fig. 2 Attackers Vs Energy consumption

D. *Transmission range Vs Energy Consumption*

Fig. 3 illustrates the energy consumption measured for PSOGD and GD when the range of communication between the nodes is varied. The node energy consumed for localization when applied with Gradient Descent method has been observed higher than the node energy consumption with combined approach of PSO and GD. As the communication range is increased from 250 to 400m, the node energy starts decreasing proportional to the increase in node distance. The decrease in the node energy level in case of GD has been found to be from 2835.332 joules to 2644.916 joules. The combined approach experiences the difference in node energy level from 1239.852 Joules to 996.2864 Joules.

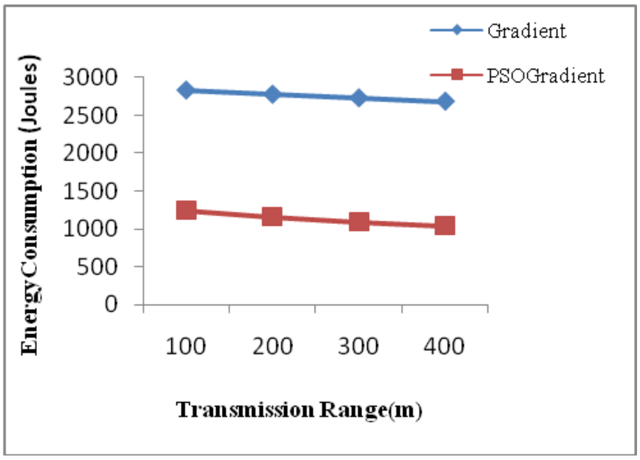

Fig. 3 Transmission range Vs Node energy consumption

E. *Range Vs Localization success*

Fig.4 shows the localization success ratio of both Gradient Descent and the combined approach of PSO and GD in the presence of the malicious nodes in the network. It has been observed from the plot that, the combined approach has better success ratio than the GD approach.

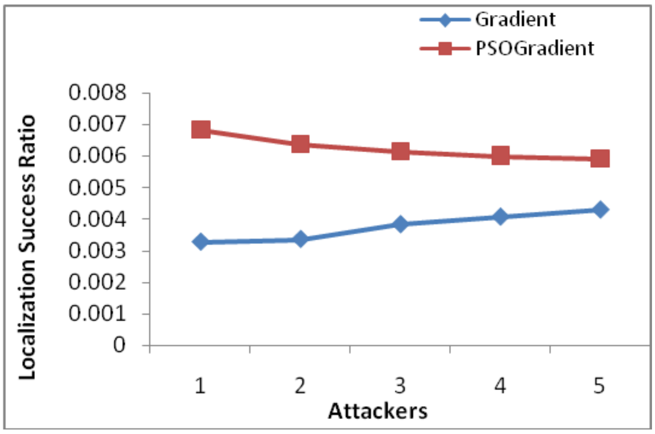

Fig.4 Range Vs. Localization Success

VI. CONCLUSION

In this paper, we have proposed a Secure Localization Using PSO and Gradient Descent Methods for Under Water Wireless Sensor Networks (UWSN). In the early stage of the localization process, GD is combined with ML method to isolate the malicious nodes from participating in localization process in the local neighborhood. Later the set of selected non-malicious nodes is further processed by PSO for finding the best possible solution in the global search space. The experiments have shown that the combined approach of PSO and GD gives better results than when they are applied separately for localization of the unknown nodes in the presence of malicious nodes. The future work has a room for further research in increasing the scalability of the localization by combining niche techniques with PSO.

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