Adaptive-Differential Evolution for Node Localization in Wireless Sensor Network

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ABSTRACT

A Wireless sensor network is composed of tens to thousands of sensor nodes which are densely deployed in a sensor field and have the capability to collect data and route data back to base station. Localization or positioning accuracy of these sensor nodes is one of the major constraints in WSN. In this paper, an Adaptive Differential Evaluation (A-DE) algorithm for localization of nodes in wireless sensor network is proposed. This paper aimed to reduce the errors in the localization of nodes in the network and improving the position accuracy of the sensor nodes. This work also compares the proposed localization results with existing Localization algorithm results in the WSN. The simulation results show that with the proposed algorithm the accuracy of localization is highly increased and the node localization errors can be reduced. The algorithm is applicable for localization in 2D as well as 3D environments.

Keywords: - *Wireless Sensor network, Adaptive- Differential Evolution (A-DE), Node Localization, Error-Reduction.*

1. INTRODUCTION

Wireless sensor networks (WSNs) are composed of numerous tiny, inexpensive, low-power sensor nodes which monitor surrounding area and measuring the desired environmental parameters [10]. These Sensor nodes collect data from their environment and send it to the Sink or Base Station in order to fulfill their tasks as shown in figure 1. Wireless sensor networks can sense, process, store and send the information in wireless environment. Advancement in technology has made WSN self-organized, cheap, small size and can communicate short distances, can be deployed in large numbers. These has made WSN to find applications in health monitoring, military surveillance, structural monitoring, road traffic management, precision agriculture, disaster management, forest fire detection, livestock monitoring and intrusion detection[1].

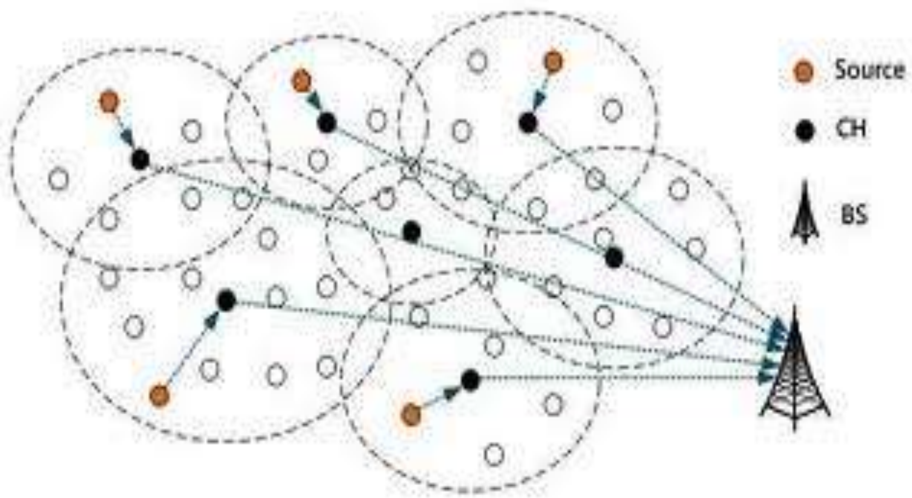

Fig- 1: Network architecture of Wireless Sensor Network

1.1 Problem Definition

Localization is a key issue for the applications of wireless sensor networks since many applications need to know the position of an unknown (a blind) node [7]. Most of the applications of wireless sensor networks require self localization of sensor node. Localization of sensor nodes refers to the awareness of location information [1]. Localization specifically aims at supplying physical co-ordinates to the sensor nodes and it totally depends upon the deployment scheme of the nodes in the network. Each sensor node communicates with each other in order to transmit data to the Base Station. There are several algorithms for efficient localization of sensor nodes like Ant-Colony Optimization, Particle Swarm Optimization (PSO), Genetic Algorithms, and Differential Evolution (DE) etc. In this paper, we present another efficient algorithm i.e. Adaptive Differential Evolution (A-DE), which improves the positioning accuracy and reduces average errors as shown in the simulation results.

2. RELATED WORK

Harikrishnan R et al., 2014 [1] introduced a D ifferential Evolution (DE)computation for node localization, giving an overview about minimization equation of wireless sensor networks localization error problem and then they discussed an approach of differential evolution for minimization of localization error in wireless sensor networks. They proposed that DE is a distributed localization algorithm based on multi alterations which uses radio signal strength for estimation.

Qiming Wei et al., 2015 [2] proposed Dynamic Differential Evolution algorithm using composite mutation strategies and parameter values self adaptation (COSADDE) to solve complex optimization problems. In COSADDE, one strategy has been chosen for each target vector to generate its trial vector in the current population with roulette. The experimental studies in this paper were concluded to be carried out on 13 global numerical optimization problems on real parameter optimization.

Hong JIANG et al., 2013 [3] presented a fast 3D node localization algorithm for Ultra Wide Band (UWB) wireless sensor network employing modified propagator method for multipath time delay estimation and 3D Chan algorithm for determining the position of sensor nodes.

Dapeng Qiao et al., 2016 [4] introduced an algorithm combining a modified differential evolution (DE) algorithm and heuristics for the situation in which the communication range value is unknown. They developed an algorithm that had a new crossover procedure, with refined procedures to produce a new generation of individuals/candidates. It is concluded that non convex constraints can be handled when using the proposed algorithm.

Hojjat Salehinejad et al., 2014 [5] proposed a novel protocol for localization of nodes in 3-D environments. They modeled the localization problem as an optimization problem. They used the micro-differential evolution with scalar random mutation factor (MDESM) algorithm to solve optimization problems.

L. M. Rasdi Rere et al., 2014 [6] evaluated two variations of adaptive DE for application of optimal image Contrast Enhancement. The main objective of their paper was to maximize the number of pixel in the edges of image, increasing the overall intensity at the edges and increase the measurement of entropy.

Changying Chen et al., 2012 [7] presented an adaptive localization structure selection method based on node density and two combined localization algorithms to satisfy the requirements of wireless sensor networks such as high-precision and low cost localization.

S. H. Thimmaiah et al., 2016 [8] proposed a RSS (Received signal strength) based localization technique and also proposed an adaptive information estimation to reduce or approximate the localization error in wireless sensor network. They also presented that the existing technique proposed so for suffered in estimating the likelihood of localization error and hence the proposed algorithm catered this.

XiuHong Wu et al., 2012 [9] introduced a novel self-adaptive localization scheme that combined range-based (RSSI) and range-free (DV-hop) algorithm for wireless sensor networks. This algorithm can not only combine the range-free and range-based advantages, but can locate nodes for nodes density sparse networks more effectively and enhance the localization accuracy.

Samaneh Hojjatoleslami et al., 2011 [10] presented a multi-objective optimization methodology for node placement in wireless sensor network design. They have investigated optimal operational modes of the nodes in order to minimize the energy consumption and meet application-specific requirements. The goal of the proposed algorithm is to find the best operational mode for each sensor in order to minimize the energy consumption by satisfying some connectivity constraints

Guo-fang Dong et al., 2010 [11] proposed self-adaptive localization algorithm based on difference for the node localization in wireless sensor network. The proposed algorithm has been simulated to obtain higher localization accuracy than differentially random distributed localization algorithm as well as the conventional self adaptive localization algorithm.

ZHAO Shuaishuai et al., 2016 [12] presented a localization algorithm based on dynamic differential evolution strategy (DDES-L). The previous position information of sensors has been used as vital anchor nodes in order to improve the convergence rate and positioning accuracy. This work also compares the proposed localization results with the genetic algorithm localization (GA-L) and least squares method (LS). The algorithm adds the distance constraint to determine the range of optimal individuals instead in overall for improving the convergence rate and localization accuracy.

P. P. Sarangi et al., 2014 [13] proposed gray- level image enhancement using DE optimization algorithm. This paper presented an attempt to demonstrate adaptability of the algorithm and its effectiveness for searching global optimal solutions to enhance the contrast and detail in a gray scale image.

Qingyun Yang et al., 2010 [14] utilized the global quickly search ability of the differential evolution algorithm, adaptive mutation, search, at last searches the optimal α, β values of beta function and this resulted in an adaptive contrast enhanced image by applying differential evolution.

3. PROPOSED ADAPTIVE DIFFERENTIAL EVOLUTION (A-DE) LOCALIZATION ALGORITHM

In this paper, we propose an Adaptive Differential Evolution (A-DE) Optimization algorithm in which we use adaptation technique with Differential Evolution for reducing the errors and increasing the positioning accuracy in the localization of the sensor nodes in the network. We present the adaptive localization structure for high-precision based on neighbor node density. The proposed algorithm is applicable for both 2D and 3D wireless sensor network architecture.

3.1 Differential Evolution

Differential Evolution (DE) is a population-based stochastic search technique that was proposed by Storm and Price in 1997 to solve real-parameter optimization problem. Differential Evolution (DE) and Genetic Algorithm (GA) have many similarities in implementation. The operators of GA are used in DE [12]. DE uses mutation, crossover, and selection operators at each generation to move its population toward the global optimum. Over the past decades, the DE algorithm has gained widespread popularity among researchers. Mutation strategy, parameters: mutation factor (F) and cross-over rate (CR) adaptation is the three most important issues of DE research [2]. It is very simple and easy to adapt DE algorithm for further applications in diverse fields. The pseudo code for DE [13] has been given below. It has been seen that in classic DE, evolution is conducted for every member of the population and the resulting individuals are saved in the memory as the next generation [2].

Psuedo Code For DE:

Set NP, F, and CR parameters of the DE
Set Gmax and gen = 1
Initialize a population of size NP of D dimensional target vectors

Evaluate fitness values of each individual vector of the population using eq. (5)
Set best = best solution with maximum fitness value
while gen ≤ Gmax do do
for each target vector Fgen(i)= 1 to NP do
Evaluate fitness value using eq. (1) for gen(i)
if Fitness(Fgen)>Fitness(best) then
best = gen(i)
end if
Randomly select index of three different
individuals such that r1 _= r2 _= r3 _= i
The mutation operation produces donor vector
d(i) = gen(r1) + F.(gen(r2) – gen(r3))
The crossover operation produces trail vector CRgen(i) using target gen(i) and donor d(i) vectors
for each parameter j = 1 to D do do
if rand ≤ CR then CRgen(j) = d(ij) then
CRgen(ij) = d(ij)
else
CRgen(ij) = Fgen(ij)
end if
end for
The selection operation produces new target vector Fgen(i) as follows
if Fitness(CRgen) > Fitness(Fgen) then
Fgen(i) = CRgen(i)
else
old target vector Fgen(i) will be retained as parent for next generation
end if
end for
gen = gen + 1
end while

3.2 Adaptive Localization Approach

When a node needs to localize itself, it primarily collects its neighbor node number (node density) before selecting a localization structure from the pre-deposited structures available to it. The cost of localization structure is directly dependent on the node density collected by the node. Errors in such adaptive structures are lesser than the pre-deposited structures [7]. Control parameter values (F and CR) are gradually self-adapted by learning from their previous experiences in generating promising solutions [2]. As in previous section we have already discussed that it is very easy to adapt DE for diverse fields. So we evaluated F and CR adaptation approach in this paper.

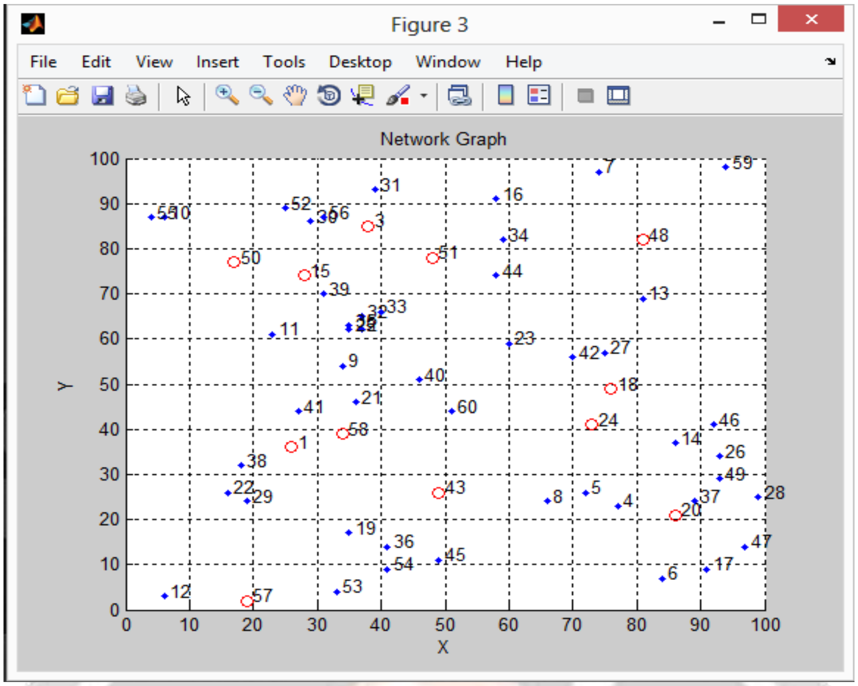

Fig.- 2: Network Graph - Node Localization

Round1: For the purpose of simulation, we have considered a square shaped network area (100 x 100 meter2), also termed as candidate pool. A dynamic strategy on the candidate pool is used for selection of the node, where the current optimal will be immediately replaced by the new competitive neighbor if it is better than the previously selected candidate. Such immediate positioning or localization of the candidates (nodes) is termed as Adaptive Localization. This approach basically depends upon self- interaction of the sensor nodes to the anchor nodes and neighbor nodes as well. The mutation strategy is effectively improved by the adaptation of control parameters F and CR as shown in Fig. 2. It shows the errors occurring in the network along with the anchor nodes corresponding to the candidate nodes. The positioning of the nodes is done specifically by identifying the anchor nodes and adapted F and CR are evaluated then.

3.3 Fitness / Objective Function

The localization of an individual highly depends upon the fitness value. A Fitness Function (f) based upon fitness value of every individual is calculated for each candidate. In our study, fitness function is scaled as follows.

Fitness= $\sum_{i=0}^{n}\sum_{1}^{n} abs\,(\text{calcpos} - \text{actualpos})$
Where calcpos= calculated position for each node i.e. defined as, $\text{calcpos}_{i,dim}$
And actualpos= actual position of the node i.e. defined as, $\text{actualpos}_{i,dim}$

4. SIMULATION RESULTS

In this section, we evaluate the simulation results as the performance evaluation of our proposed algorithm. The implementation of the performance evaluation is carried out in MATLAB environment. The performance of the network is analyzed for existing DE algorithm. The parameters taken into consideration and values are noted in the table 1 as shown below.

Table-1: Simulation Parameters Initialization

Parameters	Value
Field Size	100m X 100m
Size of Population	100
NP	50

Differential Weight(F)	0.5
Cross over Rate (CR)	0.7
Fmin	0.4
Fmax	1.9
Max iter	100

Round2: The simulation parameters initialized in the form of average errors are plotted in a graph as shown in Fig. 3 below. The graph illustrates that the proposed algorithm has lower average error (AvgErr) rate as compared to the existing DE algorithm when the nodes are localized. Adaption of parameters F and CR in case of the proposed algorithm results into reduction in errors in the localization of candidates. It can be seen that the errors are significantly decreased. Hence the performance of the localization process is improved. The value of fitness function corresponds to the mutation strategy and hence it gets improved for each parameter of the candidate node.

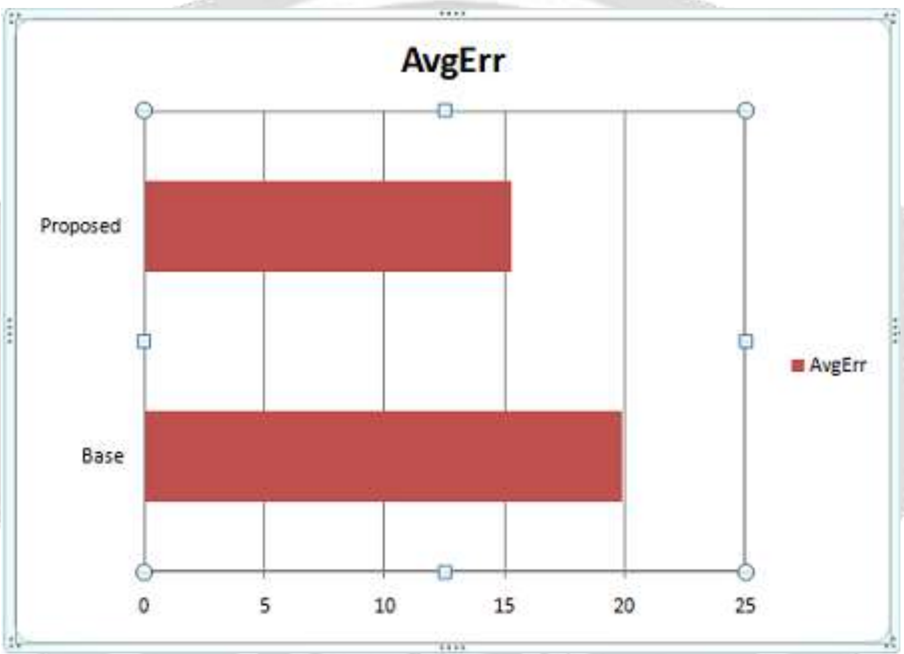

Fig.-3: Anchor Nodes VS Average Error Comparison Graph

4.1 Adaptive Parameter calculation

The objective of A-DE is to decrease the average errors in the fitness function thus generated for node localization in the network. Generally, in case of DE, the parameters F and CR are static in nature so the objective of A-DE can be achieved by adaptation of the simulation parameters such that they become dynamic and their values adapt dynamically. In this paper, the well-known logistic equation is adopted to perturb the parameters in DE during its search process. Logistic equation exhibits the sensitive dependence on initial conditions. For determining the mutation factor, the logistic equation is defined as follows [14].

$F\,(t + 1) = \mu\, .\, F\,(t)\, .\, F\,(1 - F\,(t))$ – (eq.1)

Where t is the sample, and μ is a control parameter, $0 < \mu \leq 4$. The behavior of the equation is greatly changed with the variation of μ.

After adaptation, the mutation parameters are generated as dynamic entities and the value of *F* and *CR* were updated [6] through the following equations:

Fgen = μ.*F*N*[1 – *F*N] -(eq.2)
Cgen = μ.*CR*N*[1 – *CR*N] (9) -(eq. 3)

Where Fgen and Cgen is updated value for parameter F and CR respectively.

Consider, E is the error found in localizing the node defined as:

E= desired position- calculated position

So, Average Error in localization for n no. of nodes is given by:

AvgErr= $\sum_{i=1}^{n} E/n$ – (eq.4)

Round3: The simulation parameters in the form of average errors are evaluated with the approach as shown in table 2 below. The performance depends upon decrease in average errors (AvgErr) for both algorithms. We have implemented our approach in terminals of percentage dynamics i.e. on a count of 10% in each round for both algorithms. The result from equation (4) is taken into consideration for localization's fitness average errors. The table given below is considered for plotting graph (fig. 4) of comparison in average errors.

Table-2: Simulation Parameters with proposed approach

Anchor %	10%	20%	30%	40%	50%	Avg Error
Base	20.7495	20.5441	20.9603	16.9882	20.1708	19.88258
Proposed	15.1174	14.2278	16.6988	15.1136	15.12	15.25552

Fig. 4 shows the comparison of errors found in the implementation of DE and A-DE algorithm. The simulation is done in term of round. For 100*100 numbers of nodes, average errors in positioning of nodes with DE and A-DE are drawn in a graph with respect to the anchor % which describes the correspondence of anchor node to each candidate node. When the proposed algorithm is implemented, the average error count percentile is less than that of the existing algorithm. The mutation strategy for DE depends upon the anchor % versus average error graph given below. The comparative analysis illustrates the difference in the average error count.

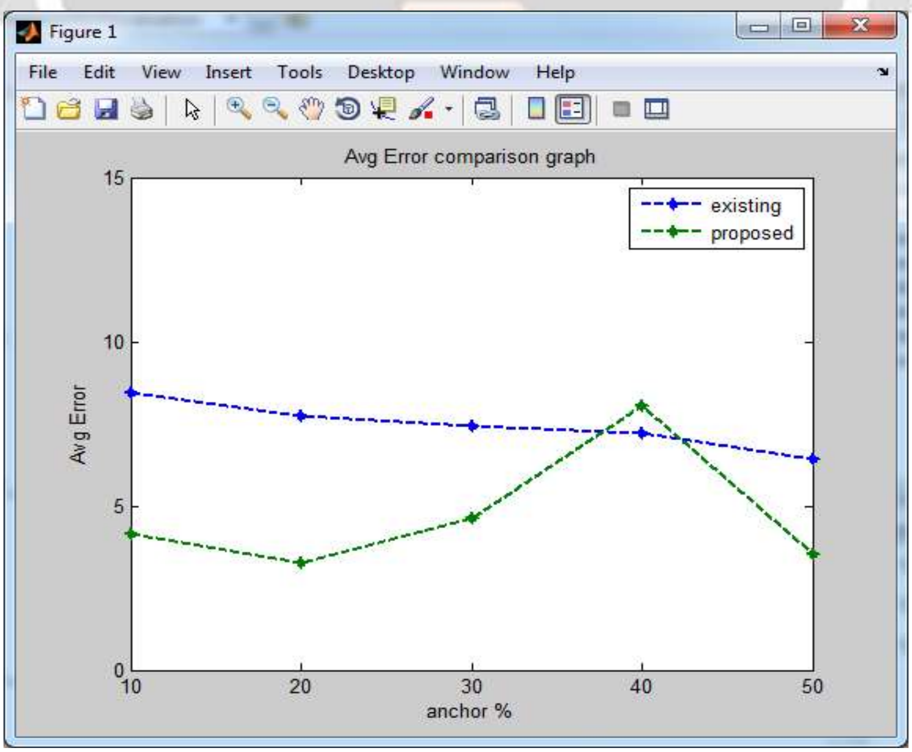

Fig.-4: Differential Error Comparison Graph

From the graphs it is evident that the performance of A-DE is better than DE algorithm. Average errors occurring in the implementation of both localization algorithms have diverse values. The fitness function is calculated by summarizing the mutation strategy and parameters and getting it plotted against the number of rounds. Performance of the network provides the outlook of localization of the network at any stage. Reduction in errors and positioning accuracy are achieved in the proposed algorithm's implementation. Localizing nodes in the candidate pool correspond to their anchor node and neighbor density.

5. CONCLUSION

In this paper, Adaptive Differential Evolution Algorithm for node localization in wireless sensor network is proposed. It has been designed to increase the localization accuracy by decreasing the errors in the network. The proposed algorithm keeps track of the anchor nodes and the selection is done to have the best results for the given scenario which includes lower average errors and higher position accuracy in the network localization phenomenon, as shown in the simulation results. Key idea to the proposed algorithm is to adapt the mutation parameters of the Localization in the WSN network. This algorithm can be further implemented for heterogeneous 3D wireless sensor networks.

6. REFERENCES

[1]. R. Harikrishnan, V. J. S. Kumar and P. S. Ponmalar, "Differential evolution approach for localization in wireless sensor networks," *2014 IEEE International Conference on Computational Intelligence and Computing Research*, Coimbatore, 2014, pp. 1-4

[2]. Q. Wei and X. Qiu, "Dynamic Differential Evolution algorithm with composite strategies and parameter values self-adaption," *2015 Seventh International Conference on Advanced Computational Intelligence (ICACI)*, Wuyi, 2015, pp. 271-274.

[3]. H. Jiang, Y. Zhang, H. Cui and C. Liu, "Fast three-dimensional node localization in UWB wireless sensor network using propagator method digest of technical papers," *2013 IEEE International Conference on Consumer Electronics (ICCE)*, Las Vegas, NV, 2013, pp. 627-628.

[4]. D. Qiao and G. K. H. Pang, "A Modified Differential Evolution With Heuristic Algorithm for Non convex Optimization on Sensor Network Localization," in *IEEE Transactions on Vehicular Technology*, vol. 65, no. 3, pp. 1676-1689, March 2016.

[5]. H. Salehinejad, R. Zadeh, R. Liscano and S. Rahnamayan, "3D localization in large-scale Wireless Sensor Networks: A micro-differential evolution approach," *2014 IEEE 25th Annual International Symposium on Personal, Indoor, and Mobile Radio Communication (PIMRC)*, Washington DC, 2014, pp. 1824-1828.

[6]. L. M. Rasdi Rere, M. Ivan Fanany, A. Murni "Adaptive DE based on chaotic sequences and random adjustment for image contrast enhancement," 2014 International Conference of Advanced Informatics: Concept, Theory and Application (ICAICTA)., pp. 220-225.

[7]. C. Chen, X. Yang, Q. Guo, Y. Fu and J. Lv, "An adaptive node localization approach for complex localization requirements in wireless sensor networks," *2012 2nd Australian Control Conference*, Sydney, NSW, 2012, pp. 192-196.

[8]. S. H. Thimmaiah and G. Mahadevan, "An adaptive localization error minimization approach for wireless sensor network," *2016 3rd International Conference on Devices, Circuits and Systems (ICDCS)*, Coimbatore, 2016, pp. 170-173.

[9]. X. Wu, Z. Wang and C. Li, "A Novel Self-Adaptive Localization Scheme in Wireless Sensor Networks," *2012 8th International Conference on Wireless Communications, Networking and Mobile Computing*, Shanghai, China, 2012, pp. 1-4.

[10]. S. Hojjatoleslami, V. Aghazarian and A. Aliabadi, "DE Based Node Placement Optimization for Wireless Sensor Networks," *2011 3rd International Workshop on Intelligent Systems and Applications*, Wuhan, 2011, pp. 1-4.

[11]. G. f. Dong, L. Chang, G. Fei, W. s. Wang, X. Niu and P. Gong, "Performance enhancement of localization in wireless sensor network by self-adaptive algorithm based on difference," *2010 Global Mobile Congress*, Shanghai, 2010, pp. 1-5.

[12]. S. Zhao, S. Chai and B. Zhang, "Dynamic differential evolution strategy localization for Wireless Sensor Networks in three-dimensional space," *2016 35th Chinese Control Conference (CCC)*, Chengdu, 2016, pp. 8423-8427.

[13] P.P. Sarangi, B.S.P. Mishra, B. Majhi and S. Dehuri, "Gray-level Image Enhancement Using Differential Evolution Optimization Algorithm", 2014 International Conference on Signal Processing and Integrated Networks (SPIN), pp. 95-99.

[14] Qingyun Yang," An Adaptive Image Contrast Enhancement based on Differential Evolution" 2010 3rd International Conference on Image and Signal Processing (CISP2010), pp. 631-634.