ARTICLE IN PRESS

Computers and Electrical Engineering xxx (2015) xxx–xxx

Contents lists available at ScienceDirect

Computers and Electrical Engineering

journal homepage: www.elsevier.com/locate/compeleceng

Rearrangement of mobile wireless sensor nodes for coverage maximization based on immune node deployment algorithm ☆

Mohammed Abo-Zahhad [a], Sabah M. Ahmed [a], Nabil Sabor [a,b,*], Shigenobu Sasaki [b]

[a] Electrical and Electronics Engineering Department, Faculty of Engineering, Assiut University, Assiut, Egypt
[b] Department of Electrical and Electronic Engineering, Niigata University, Niigata 950-2181, Japan

ARTICLE INFO

Article history:
Received 8 April 2014
Received in revised form 6 April 2015
Accepted 6 April 2015
Available online xxxx

Keywords:
Wireless mobile sensor network
Coverage holes
Multi-objective immune algorithm
Deployment strategies
Connectivity
Mobility cost

ABSTRACT

One of the primary objectives of Wireless Sensor Network (WSN) is to provide full coverage of a sensing field as long as possible. The deployment strategy of sensor nodes in the sensor field is the most critical factor related to the network coverage. However, the traditional deployment methods can cause coverage holes in the sensing field. Therefore, this paper proposes a new deployment method based on Multi-objective Immune Algorithm (MIA) and binary sensing model to alleviate these coverage holes. MIA is adopted here to maximize the coverage area of WSN by rearranging the mobile sensors based on limiting their mobility within their communication range to preserve the connectivity among them. The performance of the proposed algorithm is compared with the previous algorithms using Matlab simulation for different network environments with and without obstacles. Simulation results show that the proposed algorithm improves the coverage area and the mobility cost of WSN.

1. Introduction

A Wireless Sensor Network (WSN) is a distributed system which is composed of tiny, low-cost, battery-operated sensor nodes that collaborate together for the purpose of achieving a certain task. For instance, WSNs can be used for environment and habitat monitoring, traffic measurement on roads, vehicle tracking and personnel tracking inside buildings [1]. Coverage is one of the most important performance metrics for Wireless Sensor Networks (WSNs) since it reflects how well a sensor field is monitored. The coverage problem in WSN has been addressed either as a target coverage or an area coverage [2]. The target coverage algorithms are adopted to maximize the number of targets that could be covered based on assumption that the sensing field is divided into targets [3,4]. On the other hand, the area coverage algorithms are used to maximize the covered area of the whole sensing field [5–11].

The deployment strategy of sensor nodes in the sensor field is the most critical factor related to the network coverage. The sensor nodes can be deployed either deterministic or random. A deterministic deployment may be feasible in friendly and accessible environments. While, a random deployment is usually preferred in large scale WSNs not only because it is easy and less expensive, but also it might be the only choice in hostile environments such as battle field or forest environment.

☆ Reviews processed and approved for publication by the Editor-in-Chief.

* Corresponding author at: Electrical and Electronics Engineering Department, Faculty of Engineering, Assiut University, Assiut, Egypt.
E-mail addresses: zahhad@yahoo.com (M. Abo-Zahhad), sabahma@yahoo.com (S.M. Ahmed), nabil_sabor@aun.edu.eg (N. Sabor), sasakish@eng.niigata-u.ac.jp (S. Sasaki).

http://dx.doi.org/10.1016/j.compeleceng.2015.04.003
0045-7906/© 2015 Elsevier Ltd. All rights reserved.

However, random deployment of the sensor nodes can cause coverage holes in the sensor field; therefore, in most cases, random deployment is not guaranteed to be efficient for achieving the maximum coverage [4–7].

Solution of the coverage holes' problem depends on how the sensor nodes are rearranged with respect to each other to maximize the coverage area and also prolongs the operational life of the individual nodes with limiting the mobility cost. This is Non-deterministic Polynomial-time hard (NP-hard) problem [12,13]. Therefore, a new deployment algorithm based on Multi-objective Immune Algorithm (MIA) [14–16] and binary sensing model is proposed here to solve the above mentioned problem. The proposed algorithm utilizes the MIA to rearrange the random deployed sensor nodes based on maximizing the coverage area and minimizing the dissipated energy during the movement process. Moreover, the proposed deployment algorithm preserves the connectivity among the sensors by limiting their mobility within their communication range. The paper is organized as follows. Section 2 is a literature survey about various deployment algorithms. The network and sensing models and the objectives of the proposed algorithm are described in Section 3. Section 4 explains the proposed immune node deployment algorithm and how the multi-objective immune algorithm is used to maximize the covered area and minimizes the consumed energy during the movement process. In Section 5, the simulation results and discussion are given. Finally, Section 6 offers some conclusions.

2. Related work

Many deployment algorithms have been developed in literature [1] and [3–11] to solve the problem of coverage holes. The developed deployment algorithms are based on introducing the mobility to some sensor nodes or to all sensor nodes in the sensor field in order to improve the coverage of WSN. In [1], authors used a genetic algorithm with introducing the mobility to all sensor nodes in the network in order to provide the trade-off between coverage and nodes' traveled distance. A real-time genetic algorithm was developed in [3] to find the suitable direction of node locomotion, considering either coverage of the target area or estimation of the optimum energy consumption. While in [4], authors exploited the genetic algorithm to maximize the network coverage and to alleviate the coverage holes by finding the minimum number of additional mobile nodes and their best positions in the sensing field. Particle Swarm Optimization (PSO)-based deployment approach was presented in [5] to maximize the network coverage rate based on finding positions of the mobile sensor nodes. Nevertheless, the cost of mobility is not considered here.

Authors in [6] introduced limited mobility based coverage algorithm for the multi-hop WSNs by identifying the redundant sensing regions during the post deployed scenarios and maintain the network with limited mobility. Decision of mobility of the nodes among immediate neighbors of a dead node is totally autonomous and distributed, and it is made to maintain the network without disturbing the existing coverage and connectivity. A number of distributed algorithms for the deployment of mobile nodes were adopted in [7] to improve an irregular initial deployment of nodes and maximizes the network coverage. The first one is Distributed Self-Spreading Algorithm (DSSA). DSSA is used to improve the network lifetime and the coverage rate by introducing the mobility to all sensor nodes. The Intelligent Deployment and Clustering Algorithm (IDCA) is the second algorithm adopted for clustering WSN based on peer-to-peer mode. In peer-to-peer algorithm, each node moves itself to coverage holes to increase the network coverage rate and to prolong the network lifetime. Finally, the third algorithm introduced in [7] is a Voronoi Diagrams-based Deployment Algorithm (VDDA). This algorithm uses a distributed fashion in which each node determines how long it can survive and which action is more useful to prolong the network lifetime during deployment.

In [8], a two-phase Wireless Sensor Network Particle Swarm Optimization (WSNPSO) algorithm was presented to enhance the network coverage and the moving energy consumption. The objectives of this algorithm are achieved in separate phases with coverage maximization in the first phase while energy conservation in the second phase. An optimization scheme based on a multi-objective evolution algorithm is adopted in [9] to adjust the positions and the sensing radius of the sensor nodes to increase the network coverage rate and to reduce the sensing energy consumption and the redundant coverage. A coverage optimization strategy based on the evolution of Multi-particle Particle Swarm Optimization (MPSO) has been developed in [10] to improve the network performance and the network coverage rate. MPSO depends on adopting a number of particles independently searching for solutions' space to improve stability of the algorithm.

In [11] Biogeography-Based Optimization (BBO) algorithm has been adopted to improve the WSN coverage after initial deployment of the sensors. However, this algorithm has slow convergence. So, a Virtual Force (VF) algorithm is incorporated to improve the convergence speed of BBO algorithm. Moreover, VF-BBO algorithm outperforms BBO algorithm in the coverage area.

3. Network and sensing models and objectives of the proposed algorithm

In this section, we state some assumptions about the sensor network model. Furthermore, the binary sensing model and the objectives of the proposed algorithm will be discussed.

3.1. Network model

To develop the proposed algorithm, the following assumptions about the sensor nodes are fixed:

Please cite this article in press as: Abo-Zahhad M et al. Rearrangement of mobile wireless sensor nodes for coverage maximization based on immune node deployment algorithm. Comput Electr Eng (2015), http://dx.doi.org/10.1016/j.compeleceng.2015.04.003

- The coverage of each sensor node is a circle with radius R_s.
- All sensors have the same coverage radius (R_s) and the same communication range (R_c).
- All sensors are mobile and location-aware using localization algorithms [17,18].
- Obstacles inside the sensing field can be detected by the sensor nodes.

3.2. Binary sensing model

The sensing model used here is a binary model, which is supposed to be covered as much as possible. This means that the area within the sensing range can be counted as covered with a probability of 1 and the area out of the sensing range will be set as 0 since it cannot be covered. The sensing field is considered to be $m \times n$ grids, and each grid size is equal to 1 as shown in Fig. 1. The coverage of the whole area is proportional to the grid points that can be covered. Considering the grid point $G(x, y)$, the possibility that it can be sensed by a sensor node $s_i(x_i, y_i)$ is described by [5–7]:

$$P(x,y,s_i) = \begin{cases} 1, & if \sqrt{(x-x_i)^2 + (y-y_i)^2} \leqslant R_s \\ 0, & otherwise \end{cases} \tag{1}$$

3.3. Objectives of the proposed deployment algorithm

The proposed algorithm rearranges the random deployed sensor nodes based on maximizing the network coverage and minimizing the dissipated energy during the movement process.

3.3.1. Coverage area objective

Assuming that a WSN consists of N Mobile Sensor Nodes (MSNs) (i.e. $S = \{s_1, s_2, \ldots, s_N\}$), the probability that a point $G(x, y)$ is covered can be written as:

$$P(x,y,S) = 1 - \prod_{i=1}^{N}(1 - P(x,y,s_i)) \tag{2}$$

It should be pointed out that the area covered by each sensor is $A_{s_i} = \pi R_s^2$. So, the maximum covered area is a union all areas of the sensor nodes within the network and given by:

$$A_{\max}(S) = \bigcup_{i=1}^{N} A_{s_i} \tag{3}$$

Due to the boundaries of the sensor field and the obstacles in the sensor field, the total covered area ($A_{Cov}(S)$) is less than or equal to $A_{\max}(S)$ and given by:

$$A_{Cov}(S) = \sum_{x=1}^{m}\sum_{y=1}^{n} P(x,y,S) \leqslant A_{\max}(S) \tag{4}$$

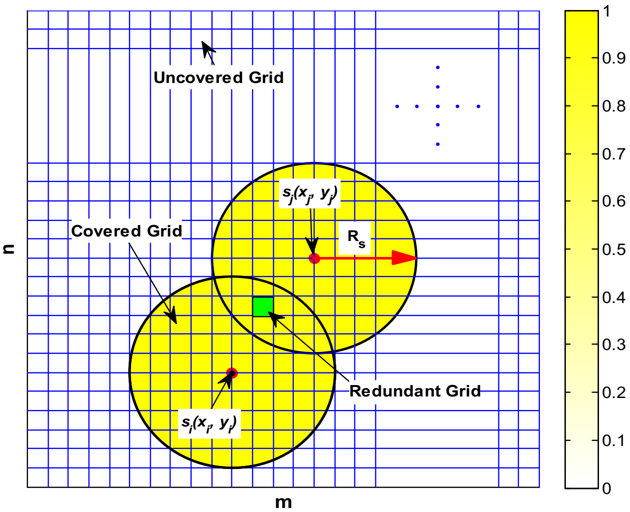


Fig. 1. Binary sensing model.

and the uncovered area is $A_{Uncov}(S) = A_{tot} - A_{Cov}(S)$. As a result, the coverage ratio is given by:

$$R_{Cov}(S) = \frac{A_{Cov}(S)}{A_{tot}} = \frac{\sum_{x=1}^{m}\sum_{y=1}^{n} P(x,y,S)}{m \times n} \tag{5}$$

where A_{tot} is the total area of the sensing field. The first objective considered in the proposed algorithm is the coverage problem. The main aim of the proposed algorithm is the maximization of the coverage area by minimizing the uncovered area ratio ($R_{Uncov}(S)$) as follows:

$$\text{minimize } (f_1 = R_{Uncov}(S) = 1 - R_{Cov}(S)) \tag{6}$$

The probability that a grid point $G(x, y)$ is covered by more than one sensor node as shown in Fig. 1 is given by:

$$P_{red}(x,y,S) = \begin{cases} 1, & \text{if } (x,y) \in s_i \text{ and } (x,y) \in s_j; i,j \in [1,N];\ i \neq j \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

The redundant covered area rate of MSNs in the sensor field is given by:

$$R_{red}(S) = \frac{\sum_{x=1}^{m}\sum_{y=1}^{n} P_{red}(x,y,S)}{A_{tot}} \tag{8}$$

3.3.2. Mobility cost objective

Since the mobile sensors consume more energy in mobility, the second objective considered in the proposed algorithm is limiting the mobility of the sensor nodes within their communication range (R_c) to preserve the connectivity among them. This has been carried out by minimizing the moved distances of all sensor nodes relative to R_c as follows:

$$\text{minimize } \left(f_2 = \frac{\sqrt{\left(\sum_{i=1}^{N} d_i^2\right)/N}}{R_c} \right) \tag{9}$$

where $d_i = \sqrt{(x_{fin} - x_{int})^2 + (y_{fin} - y_{int})^2}$ is the distance between the initial position of the i^{th} sensor node $s_i(x_{int}, y_{int})$ and final position of the same node $s_i(x_{fin}, y_{fin})$. The communication range is set as twice of the sensing radius (i.e. $R_c = 2R_s$) to maintain the connectivity among MSNs according to [2].

4. Immune nodes deployment algorithm

Rearrangement of MSNs in the sensor field to remit the coverage holes with limited mobility cost is NP-hard Problem [12,13]. Therefore, the proposed deployment method utilizes the Multi-objective Immune Algorithm (MIA) [14–16] to solve this problem. MIA mimics the antigen–antibody reaction of the immune system in mammals. The antigen and the antibody in the MIA are equivalent to the objective function and the feasible solution for a conventional optimization problem. The proposed algorithm employs the MIA to overcome the coverage holes and further maximizes the network coverage by rearranging the mobile sensor nodes based on limiting their mobility within their R_c to preserve the connectivity among them. Initially, the Base Station (BS) broadcasts a short message contains its location to request the ID and initial position of all MSNs in the sensor field. Based on the feedback information, BS uses the proposed algorithm to find the optimal positions of MSNs based on maximizing the coverage area while at the same time the mobility cost of the mobile nodes is minimized. Fig. 2 illustrates the flow chart of the proposed deployment algorithm. The main steps of the proposed algorithm are stated in pseudo code that shown in Fig. 3 and will describe in the following:

4.1. Generation of antibody population

Finding the optimal positions of MSNs is important issue to improve the network coverage. Based on the collected information from sensor nodes, BS generates a population pool of p_s positions' antibodies (PAs) by encoding the positions of nodes using the real coding representation. Each position antibody (PA) contains *2N* genes. First N genes represent the x locations of nodes, and the next N genes represent the y locations of nodes. Table 1 shows PA representation of N sensor nodes.

4.2. Objective function evaluation

The aim of the proposed deployment algorithm is finding the optimal positions of MSNs to maximize the covered area and minimizes the mobility cost based on minimizing the uncovered area ratio f_1 and the moving distances of all sensor nodes f_2 for each PA as follows:

$$\text{minimize } (F(PA) = \alpha f_1 + (1-\alpha) f_2) \tag{10}$$

The value of α ($0 \leqslant \alpha \leqslant 1$) is application-dependent. It indicates which factor is more important to be considered.

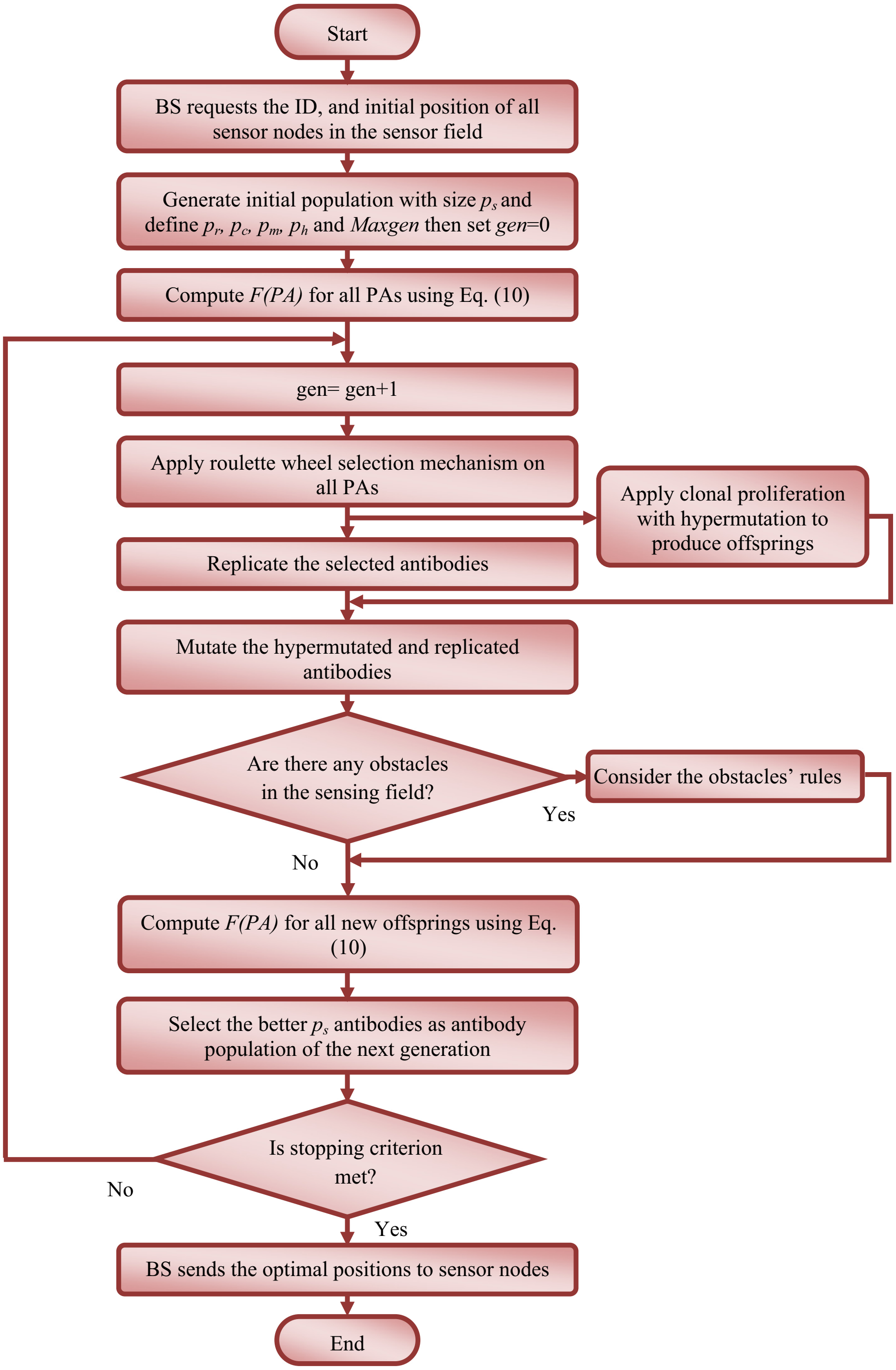


Fig. 2. Flow chart of immune node deployment algorithm.

If there are obstacles in the sensor field, the proposed algorithm checks whether the obstacle blocks the sensor node or not and takes into account the following obstacles' rules:

Rule 1: If an obstacle is located between a sensor node and a grid point, the grid point is not considered to be covered by that sensor node as shown in Fig. 4a.

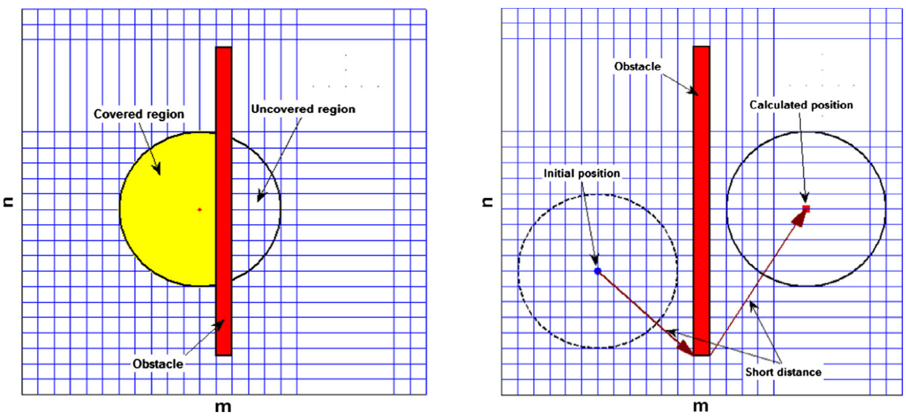
Rule 2: In case of the obstacle lays between the initial and the calculated positions of the sensor node, it is blocked by the obstacle. Thus, the moved distance of that sensor node is calculated as the shortest distance required for the node to go around the obstacle as shown in Fig. 4b.

```
Request (ID, x, y);                         % short message to request ID and initial position of each node
Set (N, Rs, field size);                    % Network Initialization
Set (ps, pr, pc, ph, pm, Maxgen) ;          % Set MIA parameters
gen=0;                                      % Initialization of generations counter
Antpop=Initial_pop(ps, 2N);                 % Construct the initial population ps×2N
Evaluuate (Antpop);                         % Evaluate the parent population
While (stopping criterion is false)
    gen=gen+1;                              % Increment the number of generations
    Antpop_sel=RWS_Selection(Antpop);       % Roulette wheel selection
    Antpop_rep=Replication (Antpop_sel);    % Selection of better antibodies
    Antpop_hyper=Clon_Hypermut(Antpop_sel); % Clonal with Hypermutation operation
    Antpop_tot=[Antpop_rep, Antpop_hyper];
    Antpop_child=Mutation(Antpop_tot);      % Mutation Operation
    Evaluuate (Antpop_child);               % Evaluate the child population
    % Selection of better antibodies to be population for next generation
    Antpop=Construct_pop(Antpop, Antpop_child);
End
Send (the optimal positions to the sensor nodes);   % Send the calculated positions to the nodes
```

Fig. 3. Pseudo code of the proposed algorithm.

Table 1
Positions Antibody representation of N sensor nodes.

	x-locations				y- locations			
Positions' Antibody (PA)	P_1	P_2	...	P_N	P_{N+1}	P_{N+2}	...	P_{2N}
	x_1	x_2	...	x_N	y_1	y_2	...	y_N



(a) Obstacle rule 1 (b) Obstacle rule 2

Fig. 4. Obstacles' rules.

4.3. Selection

The roulette wheel selection [15] is employed in immune based algorithms for antibodies reproduction. Its basic idea is to determine the selection probability for each sensor's position antibody (individual) in proportion to its fitness value ($1/F(PA)$) as shown in Fig. 5. PAs with higher fitness values are more likely to be selected as the parent antibodies that generate offsprings in the next step.

4.4. Replication

Replication operation is applied to select better ($p_r \times p_s$) PAs based on the replication rate (p_r) by sorting them according to their objective function values ($F(PA)$) in ascending order. Then, the first ($p_r \times p_s$) antibodies are selected to generate offsprings.

Please cite this article in press as: Abo-Zahhad M et al. Rearrangement of mobile wireless sensor nodes for coverage maximization based on immune node deployment algorithm. Comput Electr Eng (2015), http://dx.doi.org/10.1016/j.compeleceng.2015.04.003

4.5. Clonal proliferation within hypermutation

The clonal proliferation operation is applied to the selected parent antibodies using the roulette wheel mechanism to make them proliferate and produce offsprings. Depend on the clonal selection rate (p_c), some PAs are chosen to join the clonal proliferation. Each gene in a single antibody, depending on the hypermutation rate (p_h), executes the hypermutation of convex combination. To increase the antibodies diversity in population, $\mathrm{p_h}$ has an extremely high rate than the normal mutation rate (p_m). For a given sensors' positions antibody $PA = (P_1, P_2, \ldots, P_i, \ldots, P_k, \ldots, P_{2N})$, if the gene P_i is determined to execute the hypermutation, and another gene P_k is randomly selected to join in; the resulting offspring antibody becomes $PA' = (P_1, P_2, \ldots, P_i', \ldots, P_k, \ldots, P_{2N})$, where the new gene P_i' is $P_i' = (1-\beta)P_i + \beta P_k$, and $\beta \in [0, 1]$ is a random value.

4.6. Mutation operation

The mutation operation is derived from convex set theory to provide exploration. Two genes in a single PA are randomly chosen to execute the mutation combination. For a given $PA = (P_1, P_2, \ldots, P_i, \ldots, P_k, \ldots, P_{2N})$, if the genes P_i and P_k are randomly selected for mutation depending on p_m, the resulting offspring is $PA' = (P_1, P_2, \ldots, P_i', \ldots, P_k', \ldots, P_{2N})$. The two new genes are given by $P_i' = (1-\beta)P_i + \beta P_k$ and $P_k' = \beta P_i + (1-\beta)P_k$ respectively, where $\beta \in [0, 1]$.

4.7. Construction of new antibody population

To preserve good antibodies those have minimum $F(PA)$, the initial population pool (parents) and offsprings' antibodies that generated in the current generation are sorted in ascending order based on the values of $F(PA)$. Then the first p_s positions' antibodies with minimum $F(PA)$ values are selected to construct the antibody population for the next generation.

4.8. Stopping criterion

The optimal positions of nodes are found when $F(PA)$ does not change for a certain number of generations or when the number of generations exceeds the specified maximum generations (*Maxgen*).

5. Simulation results

In this section, four experiments were conducted using Matlab 8.1 to evaluate the performance of the proposed deployment algorithm and compare it with the previous algorithms that are described in [1 and 8–11]. To eliminate the experimental error caused by randomness; each experiment was run for 20 times and the average of results is calculated. The MIA parameters adopted are set as $p_s = 40$, $p_r = 0.9$, $p_m = 0.01$, $p_c = 0.1$, $p_h = 0.3$, $\alpha = 0.9$ and Maxgen = 50.

5.1. Performance evaluation

In this experiment, the performance of the proposed algorithm is compared with MPSO [10], BBO [11] and VF-BBO [11] algorithms. For this purpose, the simulation considers 20 randomly distributed mobile nodes within $30 \times 30\ \mathrm{m}^2$ sensor field

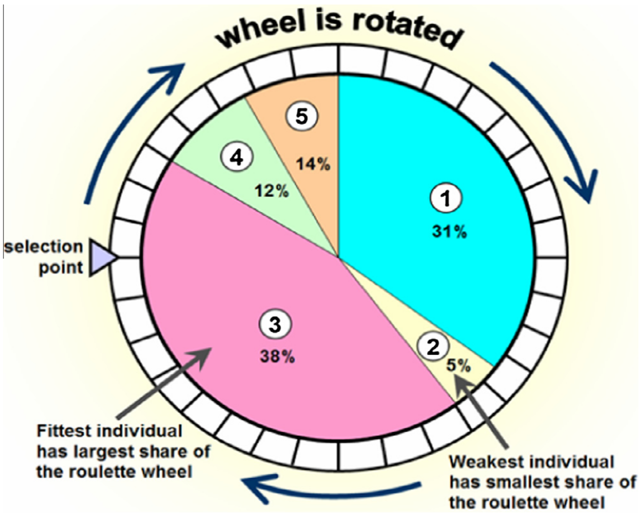
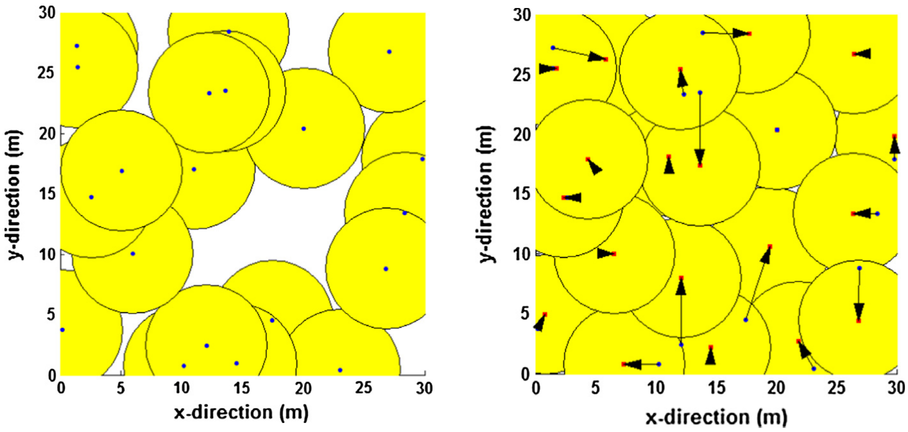


Fig. 5. Roulette wheel selection.



(a) Before rearrangement (b) After rearrangement

Fig. 6. The network coverage.

and the sensing radius R_s = 5 m. The coverage areas before and after rearrangement are shown in Fig. 6. The points marked by ●'s are the initial positions of the sensors while those marked by ■'s are their calculated positions. Arrows are drawn to represent the sensors' movement from their initial positions to their calculated positions. The minimum, maximum and average values of the covered area ratio (R_{Cov}) in 20 independent runs for the MPSO, BBO, VF-BBO algorithms and the proposed algorithm are shown in Fig. 7. From these figures, it can be observed that the average coverage ratio obtained using the proposed algorithm outperforms that obtained using MPSO, BBO and VF-BBO algorithms by 12.83%, 9.11% and 3.43% respectively. Moreover, the proposed algorithm reduces the mobility cost and preserves the connectivity among the sensors.

5.2. Convergence speed

In this experiment, we study the convergence speed of the proposed algorithm and compare it with the algorithm described in [9]. For this purpose, the simulation considers 23 randomly distributed mobile sensor nodes within $50 \times 50\ m^2$ sensor field and the sensing radius R_s = 7 m. For fair comparison with [9], Maxgen is set by 200. The coverage areas before and after rearrangement are shown in Fig. 8. Figs. 9 and 10 illustrate the covered area ratio (R_{Cov}) and the redundant covered area versus the number of generation respectively for the two algorithms.

From these figures, it can be observed that the proposed algorithm outperforms the other algorithm in terms of the convergence to the optimal coverage, and the redundant covered area. After 10 generations from starting, the coverage ratio reaches to 88.98% using the proposed algorithm and reaches to 80.1% using the other algorithm [9]. On the other hand, the redundant covered area reaches to 954 m^2 and 1103 m^2 for the proposed algorithm and the other algorithm, respectively. The proposed algorithm increases the coverage ratio gradually to 97.9% after 100 generations and decreases the redundant covered area rapidly than the other algorithm to 679.8 m^2, while the coverage ratio and the redundant covered

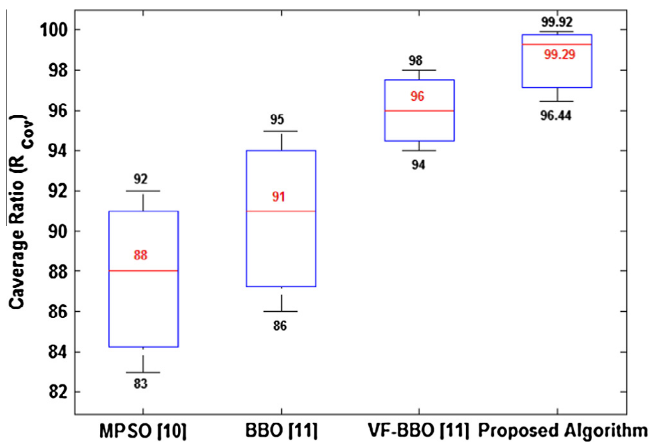
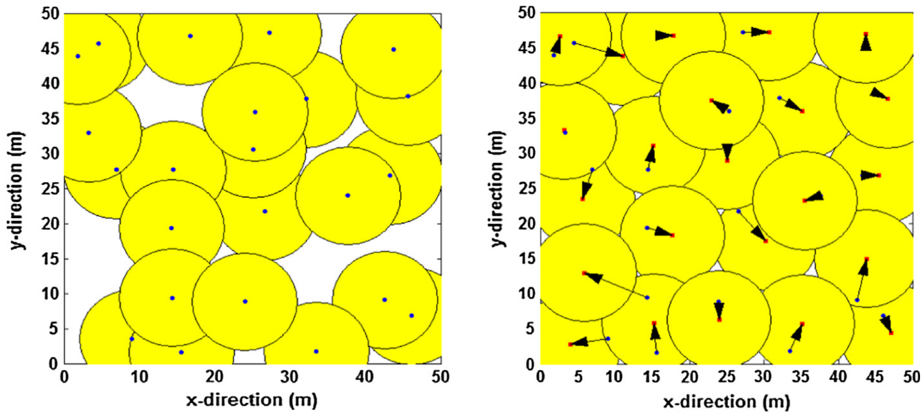


Fig. 7. Coverage results.



(a) Before rearrangement (b) After rearrangement

Fig. 8. The network coverage.

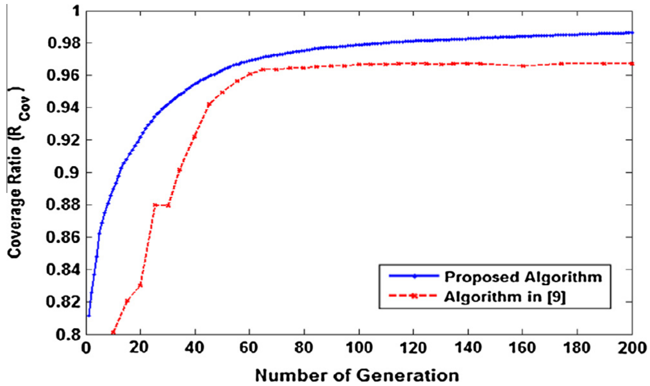


Fig. 9. The covered area ratio.

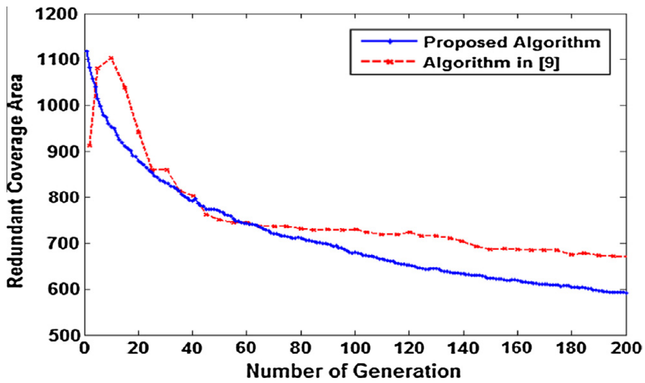
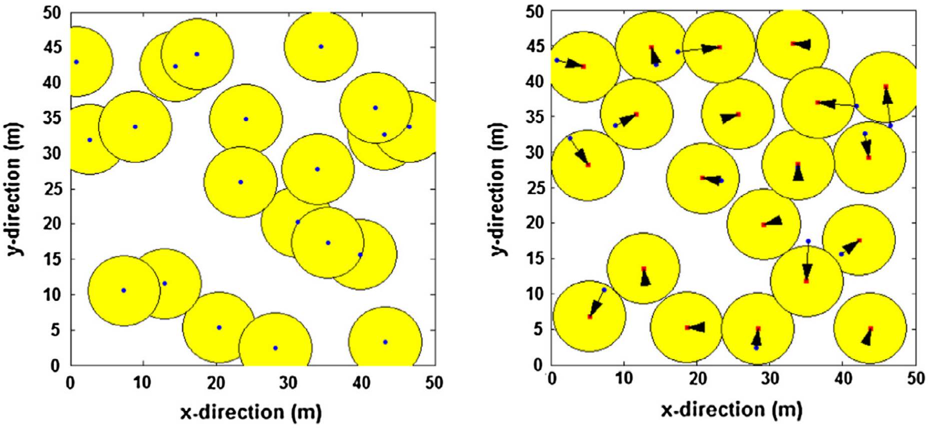


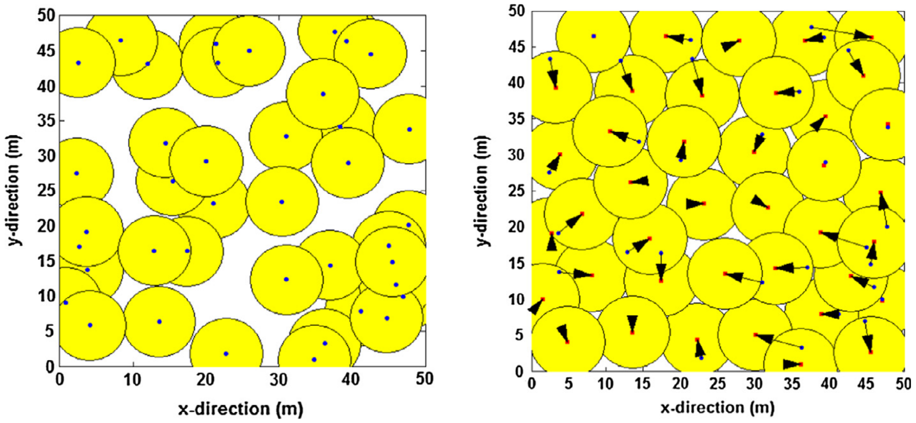
Fig. 10. The redundant covered area.

Table 2
Network specification of experiment 3.

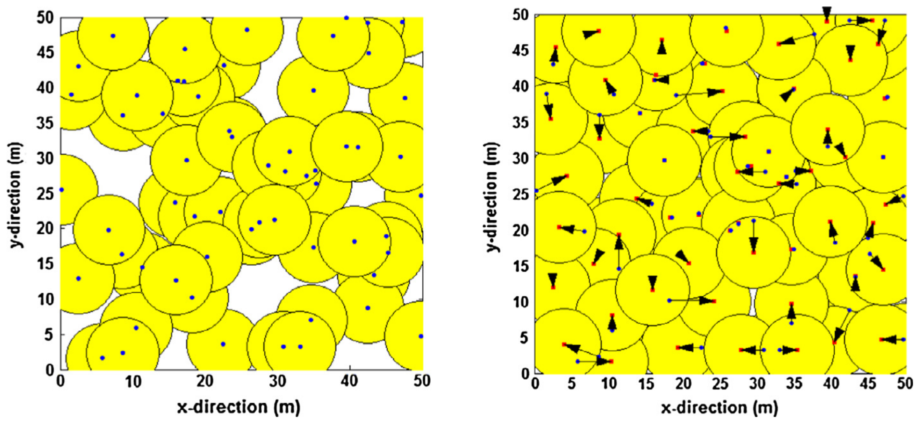
Test no.	Sensor field	R_s	No. of sensor nodes (N)
Test 1	50×50	5	20
Test 2	50×50	5	30
Test 3	50×50	5	40
Test 4	50×50	5	50
Test 5	50×50	5	60



(a) The network coverage before and after rearrangementfor test 1



(b) The network coverage before and after rearrangementfor test 3



(c) The network coverage before and after rearrangement for test 5

Fig. 11. Network coverage for tests 1, 3 and 5.

area for the algorithm in [9] reach to 96.66% and 729.5 m^2 respectively. After 200 generations, the proposed algorithm improved the coverage by 1.94%, and the redundant covered area by 13.31% as compared to the other algorithm. This means that the proposed algorithm converges to the maximum coverage faster than the other algorithm. Furthermore, it conserves energy of the sensors.

5.3. Effect of node degree

To study the effect of node degree on the performance of the proposed algorithm and compare it with WSNPSO [8], the number of sensor nodes is varied from 20 to 60 by step 10 within the same 50×50 m^2 sensor field and with fixed sensor coverage radius $R_s = 5$ m as given in Table 2. The proposed algorithm is conducted for 100 generations in each run for each test. Fig. 11 shows the network coverage for Test 1, Test 3 and Test 5 before and after rearrangement. The initial coverage ratio, the maximum coverage ratio ($A_{\max}(S)/A_{tot}$) and the covered area ratio (R_{Cov}) obtained using the proposed algorithm and WSNPSO are shown in Fig. 12. Fig. 13 shows the maximum moved distance ($d_{\max}$) of all sensor nodes in each test obtained using the proposed algorithm compared with the maximum moved distance obtained using WSNPSO algorithm.

From the obtained results, it is noticed that the proposed algorithm improves the coverage area for 5 tests by moving small number of the sensor nodes for short distances and this reduces the moving energy consumption. The proposed algorithm improves the coverage ratio by 3.67%, 5.33%, 5.31%, 4.12% and 2.58% as compared to WSNPSO algorithm for 5 tests, respectively. Moreover, it reduces the maximum moved distance by 53.43%, 29.22%, 17.24%, 26.62% and 32.73% as compared to WSNPSO algorithm for 5 tests, respectively. In Test 1, the proposed algorithm utilizes 20 mobile sensors to improve the coverage ratio from 50.5% to 62.17% with a maximum moved distance 7.726 m, while the WSNPSO covers 59.901% of the sensor field with a maximum moved distance 16.596 m. Since the number of sensor nodes increases to 60 in Test 5, the proposed algorithm increases the coverage ratio to 99.4747% with $d_{\max}$ equals 8.876 m, but the WSNPSO covers 96.9578% with $d_{\max}$ equals 13.193 m. It is observed that the proposed algorithm achieves the objectives of best deployment, because it maximizes the coverage area and also prolongs the operational life of the individual nodes by reducing the moving energy consumption. Furthermore, it ensures the connectivity among nodes because it limits the mobility of each node within its communication range (R_c).

5.4. Effect of obstacle in the sensing field

Here, we study the performance of the proposed algorithm in presence of obstacles. So the same sensing field adopted in [1] is considered, where one obstacle with size of 0.3 m by 6 m is placed in and 8 sensors are randomly distributed within 10×10 m^2 sensor field with initial coverage is 72% as shown in Fig. 14. All sensors have the same sensing range of $R_s = 2.5$ m. The MIA parameters adopted are set as $p_s = 15$, $p_r = 0.9$, $p_m = 0.05$, $p_c = 0.1$, $p_h = 0.5$, $\alpha = 0.9$ and Maxgen = 30. Table 3 shows the coverage ratio and the average moved distance (d_{avg}) of all sensors for the proposed and the genetic algorithms. The coverage network after rearrangement using the proposed algorithm is shown in Fig. 15.

The theoretical coverage of the network $((A_{tot} - \text{Obstacle Area})/A_{tot})$ is 98.2%. From the obtained results, it can be seen that the proposed algorithm performs well when the obstacles appear in the sensing field and improve the coverage toward the theoretical value. The proposed algorithm improves the coverage ratio by 2.86% as compared to the genetic algorithm. Moreover, it reduces the average moved distance by 71.88% as compared to the other algorithm. This means that the proposed algorithm limits the mobility of the sensor nodes to preserve the connectivity among them. Furthermore, it overcomes the coverage holes by rearrangement the mobile sensors and thus the coverage area is improved.

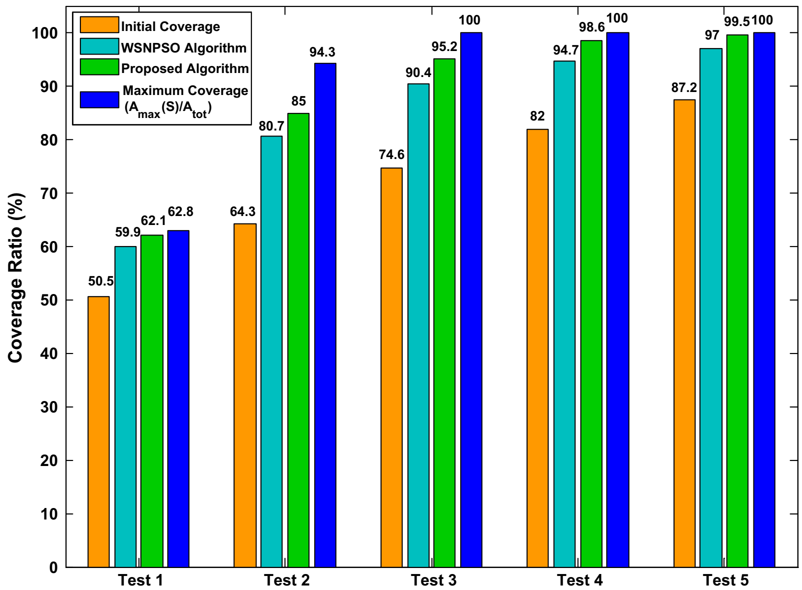


Fig. 12. Comparison of coverage ratio for five tests.

Please cite this article in press as: Abo-Zahhad M et al. Rearrangement of mobile wireless sensor nodes for coverage maximization based on immune node deployment algorithm. Comput Electr Eng (2015), http://dx.doi.org/10.1016/j.compeleceng.2015.04.003

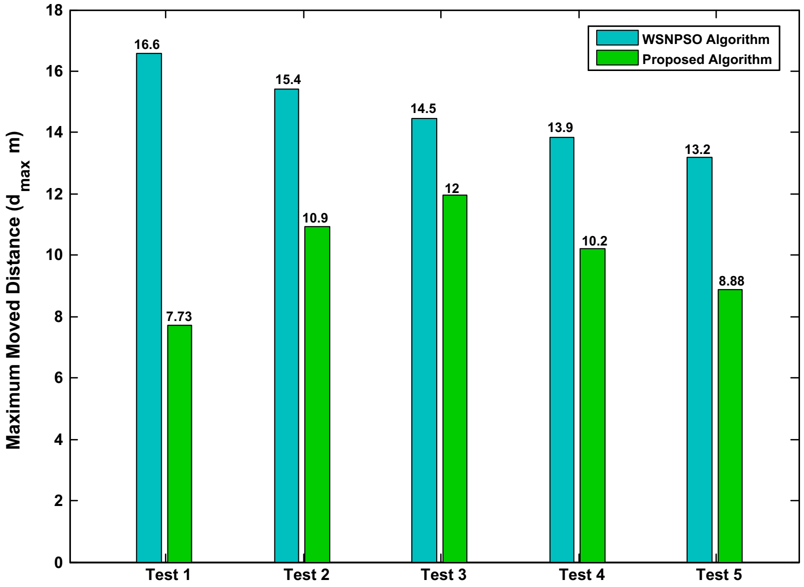


Fig. 13. Maximum moved distance for five tests.

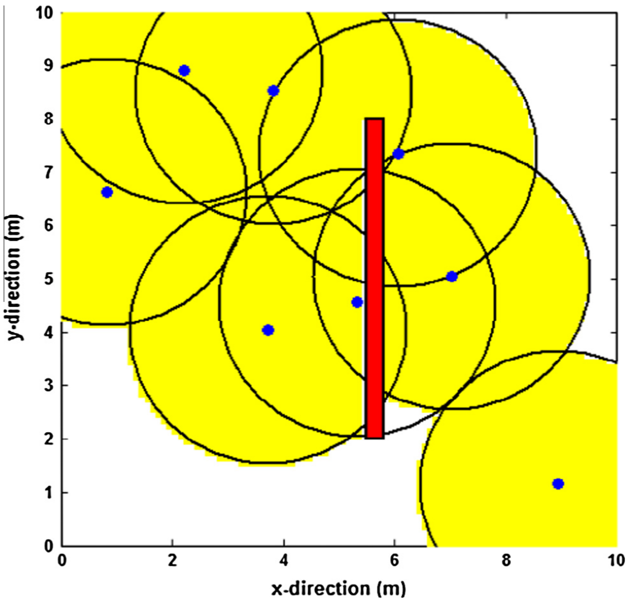


Fig. 14. Initial network coverage.

Table 3
Results of the proposed and genetic algorithms.

	Proposed algorithm	Genetic algorithm [1]
R_{Cov} (%)	94.63	92
d_{avg} (m)	1.1245	4

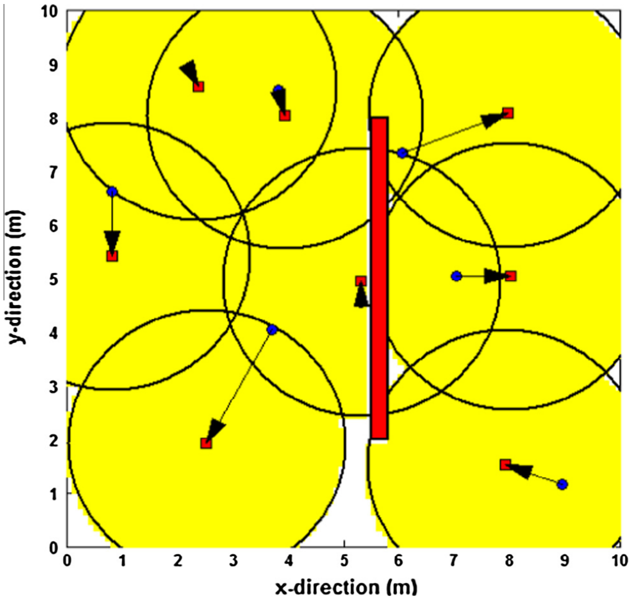


Fig. 15. Final network coverage.

6. Conclusion

Coverage has a direct effect on the network performance, thus it considered as the measure of quality of service in Wireless Sensor Networks (WSNs). The coverage issue in WSNs depends on many factors, such as the network topology, the sensing model, and the most important one is the deployment strategy. The traditional deployment methods can cause coverage holes in the sensing field. Therefore, a new centralized immune node deployment algorithm for mobile wireless sensor network has been proposed in this paper to remit the coverage holes' problem and further improve the network coverage. The proposed algorithm utilizes the multi-objective immune algorithm to rearrange the random deployed sensors based on two objectives. The first one is the maximization of the coverage area and the other objective is limiting the mobility of all sensor nodes within their communication range to preserve the connectivity among them. Simulation results for different network environments with and without obstacles showed that the proposed algorithm outperforms the other algorithms in terms of the coverage area, the redundant area, the mobility cost and the convergence speed. Moreover, it reduces the energy consumed in mobility of the mobile nodes by minimizing the moved distance of these nodes.

Acknowledgment

The authors would like to acknowledge the Egyptian Ministry of Higher Education and the Egyptian Cultural and Educational Bureau in Tokyo for funding the PhD studies of Nabil Sabor at Niigata University, Electrical and Electronic Engineering Department.

References

[1] Qu Y, Georgakopoulos SV. Relocation of wireless sensor network nodes using a genetic algorithm. in: Proceedings of 12th annual IEEE wireless and microwave technology conference (WAMICON), Clearwater Beach, 18–19 April 2011, p. 1–5.
[2] Wang B. Coverage problems in sensor networks: a survey. ACM Comput Surveys 2011;43(4):1–53.
[3] Norouzi A, Babamir FS, Zaim AH. An interactive genetic algorithm for mobile sensor networks. Stud Inform Control 2013;22(2):213–8.
[4] Banimelhem O, Mowafi M, Aljoby W. Genetic algorithm based node deployment in hybrid WSNs. Int J Commun Network 2013;5(4):273–9.
[5] Xiaoling W, Lei S, Jin W, Cho1 J, Lee S. Energy-efficient deployment of mobile sensor networks by PSO. Adv Web Network Technol Appl, Lect Notes Comput Sci 2006;3842:373–82.
[6] Sahoo PK, Sheu JP. Limited mobility coverage and connectivity maintenance protocol for wireless sensor networks. Int J Comput Networks 2011;55:2856–72.
[7] Heo N, Varshney PK. Energy-efficient deployment of intelligent mobile sensor networks. IEEE Trans Syst, Man, Cybernet – Part A: Syst Humans 2005;35(1):78–92.
[8] Aziz NAb, Mohemmed AW, Alias MY, Aziz K, Syahali S. Coverage maximization and energy conservation for mobile wireless sensor networks: a two phase particle swarm optimization algorithm. Int J Nat Comput Res 2012;3(2):43–63.
[9] Jin L, Jia J, Sun D. Node distribution optimization in mobile sensor network based on multi-objective differential evolution algorithm. In: 4th International conference on genetic and evolutionary computing, Shenzhen, China, 13–15 December 2010, p. 51–54.
[10] Zhuliang L, Yuanjin F. Research on strategy for optimizing coverage of WSNs based on multi-particle PSO. J Chin Appl Res Comput 2009;12:873–7.
[11] Song M, Yang L, Li W, Gulliver TA. Improving wireless sensor network coverage using the VF-BBO algorithm. In: IEEE Pacific rim conference on communications, computers and signal processing (PACRIM), Victoria, BC, p. 318–321; 27–29 Aug. 2013.

[12] Deepanandhini D, Amudha T. Solving job shop scheduling problems with consultant guided search metaheuristics. Int J Soft Web Sci 2013;3(1):1–6.
[13] Li D, Liu H. Sensor coverage in wireless sensor networks. In: Feng Jia, editor. Wireless networks: research, technology and applications. Nova Science Publishers; 2009. p. 3–31.
[14] Lu X, Ding Y, Hao K. Immune clonal selection algorithm for target coverage of WSNs. Int J Modell Identification Control 2011;12(1):119–24.
[15] Abo-Zahhad M, Ahmed SM, Sabor N, Al-Ajlouni AF. Design of two-dimensional recursive digital filters with specified magnitude and group delay characteristics using Taguchi-based immune algorithm. Int J Signal Imaging Syst Eng 2010;3(3):222–35.
[16] Abo-Zahhad M, Ahmed SM, Sabor N, Al-Ajlouni AF. The convergence speed of single-and multi-objective immune algorithm based optimization problems. Signal Process: An Int J 2010;4(5):247–66.
[17] Cho SY, Kim BD. Linear closed-form solution for wireless localisation with ultra-wideband/chirp spread spectrum signals based on difference of squared range measurements. IET Wireless Sensor Syst 2013;3(4):255–65.
[18] Shuai C, Reny S, Shuifeng Z. Wireless sensor network positioning based on the unilateral side of two reference nodes. Int J Comput Electric Eng 2014;40(2):367–73.

Mohammed Abo-Zahhad (SIEEEM'00) received Ph.D. degree from Kent University, UK and Assiut University, Egypt (channel system), 1988. He published 130 papers in biomedical signal processing, genetic and immune algorithms and wireless sensor networks fields. Currently he is the head of Electrical Engineering Department, since Nov. 2013 and formerly vice-dean of graduated studies, from August 2006 till July 2012.

Sabah M. Ahmed received Ph.D. degree from the Technical University of Budapest, Hungary. She published 75 papers in speech and biomedical signal processing, genetic algorithms and wireless sensor networks. Currently she is a Professor of Electronics and Communication Engineering, since Feb. 2009 and the manager of Assiut University communication and information technology training center since July 2010.

Nabil Sabor received his B.S.E.E and M.S.E.E degrees in electrical engineering in 2006 and 2011 respectively, both from Assiut University, Egypt. Since 2006, he has been with Assiut University, where he is now an Assistant Lecturer at the Department of Electronics and Communication Engineering. He published 10 papers in biomedical signal processing, genetic and immune algorithms and wireless sensor networks.

Shigenobu Sasaki received B.E., M.E. and Ph.D. degrees from Nagaoka University of Technology, Japan, in 1987, 1989 and 1993 respectively. Since 1992, he has been with Niigata University, where he is now a Professor at the Department of Electrical and Electronic Engineering. His research interests are in the area of wideband digital communications and cognitive radio technology.