Hybrid Genetic Algorithm With Haar Wavelet for Maximum Target Coverage Node Deployment in Wireless Sensor Networks

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ABSTRACT

Wireless sensor networks (WSNs) are used in industrial applications and focused on target coverage and node connectivity based WSNs. The set of sensors and targets is placed in optimal position the target coverage and node connectivity achieving maximum with limited sensor nodes. To resolve this problem, the proposed hybrid genetic algorithm combined with lifting wavelet multi-resolution principles for recognizing optimal position for sensors to cover entire targets present in the fields. The hybrid genetic algorithm randomly identifies each sensor position and 2D Haar lifting wavelet transform to improve the quality of target coverage by adjusting node position. The 2D Haar lifting decomposes the population matrix into the optimal position of sensors. Experimental results show the performance of the proposed hybrid genetic algorithm and fast local search method compared with available algorithms improves the target coverage and the number of nodes with varying and fixed sensing ranges with a different region.

KEYWORDS

Genetic Algorithm, Haar Lifting Wavelet Transform, Node Connectivity, Optimal Sensor Placement, Target Coverage, Wireless Sensor Networks

1. INTRODUCTION

The advent which enabled their deployment in wireless sensor networks (WSNs) consists of mobile and stationary sensor nodes that are spatially sensing and processing the data. It is used for monitoring physical and interacting with the surrounding environment using multiple tiny sensors (Chamam and Pierre, 2009), (Yoon and Kim, 2013), (Ouchitachen *et al.*, 2016). Sensor nodes are operating on battery power, sensors used in the unreachable area for a long period are not chargeable and unrepairable (Rajesh and Ranjitha, 2019), (Bhatia *et al.*, 2016). In the last few years, many kinds of research have established to extend the node lifetime (Ouchitachen *et al.*, 2016). Sensors act differently depending on situations while performing the intended application (Carrabs *et al.*, 2015).

DOI: 10.4018/JCIT.20210701.oa6

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Sensors mainly depend on the environmental application that differs from network deployment and the rate of energy depletion (Rajesh and Vinaygasundaram, 2014) (Chamam and Pierre, 2009), (Ghosal and Halder, 2015). There are two types of node deployment in WSNs, i.e., random, and deterministic node deployment (Ghosal and Halder, 2015). But the deployment of the hybrid networks is combined with mobile static sensors. In general, during configuration static sensor networks deployment is considered static or dynamic (Abdelkhalek *et al.*, 2015), (Vilela *et al.*, 2016). Random deployment mostly used in inaccessible environmental regions like the deep sea, volcanoes, very dangerous forest area, etc., where nodes are dropped by helicopter (Ghosal and Halder, 2015).

While deploying deterministic sensors focus on well planned accessible regions to meet predefined objectives like energy conservation, the number of nodes, the position of nodes, application of nodes, and network lifetime (Yoon and Kim, 2013), (Zhang *et al.*, 2016). The genetic algorithm (GA) is also used for optimal sensor placement for static and dynamic networks. The main objectives for optimal sensor deployment enhance or limit the mobility or energy for increasing network lifetime, sensing range to cover or monitor the maximum number of targets or objects, communication range to interact with nodes (Vilela *et al.*, 2016). The major aspects to be resolved while deploying node in an optimal position can be achieved by a limited number of sensors to cover the maximum number of targets with node connectivity.

The main contribution of this paper is as follows, initially, sensor nodes are deployed randomly in the monitoring fields to measure the quality of the number of target coverage or monitor. Based on the analysis the hybrid GA is to identify the optimal position of the sensor for modifying crossover and mutation points. A hybrid framework that consists of a GA based heuristic searches evolutionary algorithm which compromises many complex optimization problems successfully. The implementation of proposed hybrid GA is presented step by step, including initial population matrix, evaluation of fitness function for that matrix, the genetic operation like crossover and mutation, and the scheduling transition for lifting. Then local enhancement is done by a multiresolution analysis applying a lifting based wavelet transform for adjusting the GA population matrix.

The rest of this paper structured as follows. In Section 2, discuss the literature review provided for optimal sensor deployment coverage consent. Section 3 follows problem formation based on a network model and quality measure by the number of target coverage and number of node connectivity. Section 4 is about multi-resolution analysis in the form of a lifting scheme-based matrix decomposition. Section 5 deals with the proposed hybrid genetic algorithm-based node deployment in a population matrix format and enhanced by two dimensions Haar lifting wavelet transform (2DHLWT). Section 6 is describing the simulation results under ideal, more realistic scenarios and the quality of the number of target coverage or monitor. Finally, this paper concludes with the scope of the work.

2. LITERATURE REVIEW

Recently many researchers have developed different techniques to improve the quality of target coverage, node connectivity, and lifetime maximization. One of the most significant factors will directly affect coverage, node connectivity, and network lifetime by node placement.

The authors (Alia and Al-Ajouri, 2017) proposed maximum network coverage and minimum network cost are to be achieved by Harmony algorithm where it identifies the total number of sensors required and its position. The author divides the coverage probability into fully covered, partially covered, and uncovered. The quality of the target cover is measured by Harmony search parameters. The authors (Hu *et al.*, 2010) applied forward encoding scheme-based Hybrid Genetic Algorithm (HGA) and scheduling transition for point coverage and area coverage (Katti, 2019), (Hanh *et al.*, 2019) in disjoint set covers. The different features of HGA applied in the chromosomes of the population for effective scheduling transition. The novel forward encoding maximizes the gene value in all chromosomes for the quality of target coverage. The primary task of scheduling sensors transitions is to change unique incomplete set covers to complete set covers.

The randomly deployed sensors are moving inside the field and to adjust its sensing range. The authors (Abo-Zahhad *et al.*, 2016) proposed a model for identifying the optimal position for mobile sensors by redeploying and aims to network coverage and less energy dissipation for mobility and sense of sensors. The author presents centralized immune Voronoi deployment having two different phases, the initial antibody population having all the sensor location to be evaluated and sensing range are calculated for all the sensors, to identify and select the best antibodies to be replicated. The same thing is to be done in phase 2 with binary antibodies to find optimal nodes to cover the fields.

The author considered the k-coverage problematic for many sensor placements schemes. The authors (Ashouri *et al.*, 2012) explored the number of disjoint set k-coverage to the extent of the lifespan. The target is covered by the very least number of sensors called as a critical target (Katti, 2019). The same as the set of sensors covering the least covered target is called critical sensors. The author defined the triple parameters S, T, C where S, T as sensor set and target set, C is a coverage relation to use any k values for the maximum number of disjoint covers. The authors (Gupta *et al.*, 2015) used GA based node placement, it delivers k-coverage of the set of target covers and m-connectivity for nodes. The coverage and connectivity problem to be stated as three Boolean variables called target cover, node-connect, and potential position.

The authors (Liao and Ting, 2018) proposed a novel memetic algorithm based on an integer coded genetic algorithm with some local search operation for set k-cover problem. While placing the sensor the tight upper bound value is derived to integer represent. Here crossover and mutation operation are used to separate the critical sensors. The recycling operator discovers the redundant sensors, noncritical sensors in all groups, and randomly dispatch this into groups to form the covers.

The evolutionary algorithm solves many mathematical optimization problems (Hanh *et al.*, 2019). The authors (Chen *et al.*, 2015) organize the coverage methods for disjoints set algorithms, non-disjoints set algorithms, and hybrid memetic frameworks algorithms. The authors proposed disjoint set covers (DSC) and dynamic coverage maintenance (DCM) for network lifetime maximization. The hybrid memetic algorithms obtain the coverage results while finding the maximum number of DSC. The heuristic recursive algorithm (HRA) is used to run and activate a specific number of nodes to patch coverage holes that may cause the node failure and energy depletion of nodes. The authors (Vijayaraju *et al.*, 2017) proposed a hybrid memetic algorithm to generate a random population matrix containing sensor positions. This population matrix is decomposing for multi-resolution analysis to find optimal values. Here the 2D discrete Haar wavelets transform are applied for local enhancement to adjust the sensor position into optimal one.

The genetic algorithm based on a random population generation containing a sensor position (Ganesan and Rajarajeswari, 2019a). This sensor position is to be undergone to multilevel decompose using lazy lifting (Ganesan and Rajarajeswari, 2019b) and CDF 5/3 lifting (Ganesan *et al.*, 2021) based wavelet transforms to adjust the sensor position to cover maximum targets. While using the lifting scheme the local search operation to be fastened and to find the optimal sensor position.

3. PROBLEM FORMATION

3.1 Network Model

In this division, the network model formulates the coverage-connectivity-energy problem as a mathematical problem. Define the sensor field size is $A \times A$ contains N sensors $S = \{S_1, S_2, S_3, \dots, S_i, \dots, S_N\}$ with the sensing range radius set $R_s = \{R_{s1}, R_{s2}, R_{s3}, \dots, R_{si}, \dots, R_{sN}\}$ whereas $R_{si} \in (R_{s_{\min}}, R_{s_{\max}})$. All the sensors sensing range is to be adjusted within the $(R_{s_{\min}}, R_{s_{\max}})$. The communication range radius of each sensor set $R_c = \{R_{c1}, R_{c2}, R_{c3}, \dots, R_{ci}, \dots, R_{cN}\}$ which guarantees the network connectivity of nodes at least by $R_{ci} \geq 2R_{si}$. Given N sensors randomly distributed to monitor the M targets $T = \{T_1, T_2, T_3, \dots, T_i, \dots, T_M\}$ which are available in the same region, $A \times A$. Target T_i is

said to be covered or monitored if it is available in the sensing range R_{S_i} of at least one sensor. All the sensors are partition into several groups for the target covers. Where cover is defined as a sensor group that can cover all the targets. When the available sensors count is more than the available targets, every sensor may be covered to all targets. But, here $N < M$ is a lesser amount of some sensors to cover the maximum number of targets. It leads to redundant covers of targets and some sensors cover non-redundant targets.

3.2 Coverage and Connectivity Rate Calculation

This subsection provides the sensor S_i and S_j is randomly placed in the region (x_i, y_i) and (x_j, y_j) with sensing range, R_{S_i} and R_{S_j} respectively to cover the target T_t which is available in the region (x_t, y_t) . The sensor S_i monitors the target T_t and S_i connected to S_j when it satisfies the following Euclidean distance-based condition (1) and (2):

$$Cov(S_i, T_t) = \begin{cases} 1, dist(S_i, T_t) \leq R_{S_i}, \forall i, 1 \leq i \leq N, \forall t, 1 \leq t \leq M \\ 0, otherwise \end{cases} \quad (1)$$

$$Con(S_i, S_j) = \begin{cases} 1, dist(S_i, S_j) \leq R_{C_i}, \forall i, 1 \leq i \leq N, \forall j, 1 \leq j \leq N \text{ and } i \neq j \\ 0, otherwise \end{cases} \quad (2)$$

The potential position of each sensor P_{S_i} is identified by coverage of targets and connectivity of sensors when the following constraint is satisfied (3) it can be represented in the form of the given matrix:

$$P_{S_i} = \begin{cases} 1, Cov(S_i, T_t) = 1 \text{ and } Con(S_i, S_j) = 1 \\ 0, otherwise \end{cases} \quad (3)$$

$$P_{S_N \times T_M} = \begin{bmatrix} P_{1,1} & P_{1,2} & \dots & P_{1,M} \\ P_{2,1} & P_{2,2} & \dots & P_{2,M} \\ \dots & \dots & \dots & \dots \\ P_{N,1} & P_{N,2} & \dots & P_{N,M} \end{bmatrix} \quad (4)$$

The matrix can be represented as total target coverage by doing a column sum of the matrix while deploying all sensors are defined as Qoc (%) is referred to as the number of target object covered by using equation (4). Whereas to define the lifetime of every sensor node is $BS_i^l = BS_i / ES_i$. Where BS_i is the initial battery power of sensor node S_i , and ES_i is the rate of energy consumption of sensor S_i (Mini *et al.*, 2014). The network lifetime is achieved maximum by applying the upper bound configuration:

$$U = \min \left[\frac{\sum_{i=1}^N P_{S_i} \times BS_i^l}{M} \right]$$

$$Qoc(\%) = \frac{\sum_{j=1}^M \left| \frac{\sum_{i=1}^N P_{i,j}}{N} \right|}{M} \times 100 \quad (5)$$

The illustration network of size 100 x 100 containing M=16 available targets is used in Figure 1 and N=8 available number of sensors are randomly deployed in the same environmental region to monitor the targets is represented in Figure 2. The total coverage of all the sensors is acknowledged by equation (1). The coverage of all the sensors are $S1 = \{\}$, $S2 = \{\}$, $S3 = \{T9\}$, $S4 = \{T6, T15\}$, $S5 = \{T15, T16\}$, $S6 = \{T1\}$, $S7 = \{T7, T12\}$ and $S8 = \{T3, T8\}$. Randomly deployed targets and sensors shown in Figure 2 covers Qoc (%) 56.25% of targets. But it does not assure the connectivity of the sensor, and the main objective is to cover total targets, which need an optimal number of sensor placement to monitor total targets.

4. HAAR LIFTING WAVELET TRANSFORM

The picture-perfect reconstruction filter pairs of (h, g) having similar low and high pass filters after lifting scheme. Initiated from lazy wavelet lifting to multiresolution analysis with some properties (Daubechies and Sweldens, 1998). The filter pairs (h, g) are complementary when the poly-phase matrix P(z) (6) has determinant matrix value 1. Here any pairs of complementary filters (h, g) are factoring into lifting steps. To execute the Euclidean algorithm, start from even and odd values of $h_e(z)$ and $h_o(z)$ (Hasan and Wahid, 2016), (Hu and Jong, 2013):

Figure 1. Randomly deployed targets

Figure 2. Randomly deployed sensors

$$P(z) = \begin{bmatrix} h_e(z) & g_e(z) \\ h_o(z) & g_o(z) \end{bmatrix} \quad (6)$$

Un-Normalized Haar wavelet (Bamerni and Sulaifanie, 2019) is having $h(z) = 1 + z^{-1}$ synthesis low pass filter (SLPF), $\tilde{h}(z) = 1/2 + 1/2z^{-1}$ analysis low pass filter (ALPF), $\tilde{g}(z) = -1 + z^{-1}$ analysis high pass filter (AHPF), and $g(z) = -1/2 + 1/2z^{-1}$ synthesis high pass filter (SHPF), while executing the Euclidean algorithm the poly-phase matrix is given below:

$$P(z) = \begin{bmatrix} 1 & -1/2 \\ 1 & 1/2 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & -1/2 \\ 0 & 1 \end{bmatrix} \quad (7)$$

In general lifting operations are done in three steps split, predict, and update. The initial operation split is done by separate even and odd data (Hasan and Wahid, 2016), (Hu and Jong, 2013). Predict and update operation; the data to get the detail and approximate data. Haar wavelet multiresolution analysis is done in the given equation (8) to (11) to produce the detail and approx. data for each level as shown in Figure 3. The input of $X(n)$ is split into an even (X_{2l}) and odd (X_{2l+1}) half sampling sequence. Here the odd component is predicted by even component through prediction operator, then the detailed output is d_l^1 . The detailed input d_l^1 is updating through an update operator to get an approximate output S_l^1 :

$$S_l^0 = X_{2l} \quad (8)$$

Figure 3. Haar Lifting Scheme

$$d_i^0 = X_{2i+1} \quad (9)$$

$$d_i^1 = d_i^0 - S_i^0 \quad (10)$$

$$S_i^1 = S_i^0 + 1/2 d_i^1 \quad (11)$$

Here input data $N \times N$ two-dimensional matrix is applied first in row-wise followed by column-wise by Haar lifting wavelet transform represented in Figure 4. to produce LL approximation, LH, HL, and HH detailed components.

The $N \times N$ size of the LL matrix is decomposed into level by level by applying conventional 2DHLWT produced $N/2 \times N/2$ LL for the next level. After level 1, again 2DHLWT is applied to get $N/4 \times N/4$ LL matrix for level 2. $N/4 \times N/4$ matrix is decomposed to get $N/8 \times N/8$ LL. This process will be repeated up to $N=2^j$ times and represented in Figure 5.

5. GA-2D HAAR LIFTING WAVELET BASED OPTIMAL SENSOR PLACEMENT

The general search problem solution to be optimized by one of the evolutionary algorithms is the Genetic algorithm (GA). Its initial population contains randomly generated values of sensor position called chromosome in the matrix rows.

Randomly generated values are 0 to $A \times A$ whereas 100×100 . The initial population is evaluated by fitness function (5) by converting sensor position into coordinates:

$$X = \text{abs} \left(\frac{P_{i,j}}{A} \right) \text{ and } Y = (P_{i,j}) \bmod(A)$$

Figure 4. Conventional 2-D Haar Lifting Wavelet Transform

Once the initial population is evaluated by the fitness function, GA undergoes crossover, and mutation. Crossover is used to exchanges the genes among two chromosomes. Here having one or single-point crossover to be done for exchanging genes. GA generates a random value for a one-point crossover. After crossover, offspring are used to change some randomly generated gene values for mutation. Once the mutation is over the local search of the Haar lifting wavelet enhances the solution by adjusting the offspring values for the optimal position of sensors as represented in Figure 6. The framework of proposed optimal sensor placement is in given Algorithm 1:

$$pop1 = \begin{bmatrix} 9081 & 4878 & 5236 & 2931 & 2330 & 1236 & 4213 & 1168 \\ 7235 & 3436 & 6543 & 7678 & 3233 & 5667 & 8789 & 2312 \\ 786 & 1012 & 1567 & 5532 & 4666 & 7889 & 9898 & 3234 \\ 7989 & 1223 & 3318 & 8582 & 8189 & 9163 & 7371 & 6823 \\ 9136 & 3267 & 4598 & 5832 & 983 & 2312 & 6543 & 9656 \\ 657 & 1777 & 1586 & 3156 & 7237 & 7447 & 2323 & 5646 \\ 578 & 3562 & 6587 & 5545 & 4555 & 6571 & 8381 & 8682 \\ 8321 & 7980 & 5062 & 4045 & 6380 & 2390 & 973 & 5470 \end{bmatrix} \quad (12)$$

Figure 5. Haar Lifting Decompose matrix

$$pop2 = \begin{bmatrix} 8846 & 4590 & 2340 & 3888 & 4302 & 3781 & 7180 & 5240 \\ 850 & 4680 & 3057 & 9034 & 3409 & 1580 & 2003 & 1067 \\ 5003 & 5780 & 3098 & 679 & 4052 & 5040 & 2057 & 5305 \\ 5002 & 2012 & 1989 & 1990 & 4042 & 1991 & 2021 & 4590 \\ 9065 & 6640 & 6070 & 5460 & 3408 & 2379 & 4002 & 3045 \\ 7074 & 930 & 8074 & 7049 & 8905 & 1098 & 1005 & 4789 \\ 1877 & 5329 & 4280 & 5289 & 5034 & 1290 & 9076 & 3480 \\ 9667 & 4087 & 3287 & 676 & 5980 & 8092 & 7423 & 4490 \end{bmatrix} \quad (13)$$

The initial population matrix is used to evaluate the fitness function of Qoc (%) while converting into coordinates position:

Figure 6. Flowchart for Process of GA+2DHLWT

Algorithm 1. GA + Haar Lifting Wavelet transform for sensor placement

Input: N , M , T , R_{si} , and R_{Ci} entire sensor.
Output: optimal sensor position.

- 1: Start
- 2: pop = Randomly generated initial population matrix
- 3: for $i=1$: gene:
  - while $Fitness(pop) \neq TRUE$
    - $offs\_c = Crossover(pop)$.
    - $offs\_m = Mutation(offs\_c)$.
    - $pop\_ls = Local\_Search\_Haar\_Lifting(offs\_m)$.
    - $pop = Survival(pop, pop\_ls)$.
- 4: Display the position of the sensors in the matrix.
- 5: Stop

$$pop1 = \begin{bmatrix} X \\ Y \end{bmatrix} = \begin{bmatrix} 90 & 48 & 52 & 29 & 23 & 12 & 42 & 11 \\ 81 & 78 & 36 & 31 & 30 & 36 & 13 & 68 \end{bmatrix} \quad (14)$$

$$pop2 = \begin{bmatrix} X \\ Y \end{bmatrix} = \begin{bmatrix} 88 & 45 & 23 & 38 & 43 & 37 & 71 & 52 \\ 46 & 90 & 40 & 88 & 02 & 81 & 80 & 40 \end{bmatrix} \quad (15)$$

The pop 1 (X, Y) coordinates are deployed into the region Figure 2. And fitness function is 56.25% while deploying the entire sensor only 9 targets are covered. Here randomly generated one-point crossover is 5 and pop 1 and pop 2 will be changed:

$$offs1 = \begin{bmatrix} 9081 & 4878 & 5236 & 2931 & 2330 & 3781 & 7180 & 5240 \\ 7235 & 3436 & 6543 & 7678 & 3233 & 1580 & 2003 & 1067 \\ 786 & 1012 & 1567 & 5532 & 4666 & 5040 & 2057 & 5305 \\ 7989 & 1223 & 3318 & 8582 & 8189 & 1991 & 2021 & 4590 \\ 9136 & 3267 & 4598 & 5832 & 983 & 2379 & 4002 & 3045 \\ 657 & 1777 & 1586 & 3156 & 7237 & 1098 & 1005 & 4789 \\ 578 & 3562 & 6587 & 5545 & 4555 & 1290 & 9076 & 3480 \\ 8321 & 7980 & 5062 & 4045 & 6380 & 8092 & 7423 & 4490 \end{bmatrix} \quad (16)$$

$$offs2 = \begin{bmatrix} 8846 & 4590 & 2340 & 3888 & 4302 & 1236 & 4213 & 1168 \\ 850 & 4680 & 3057 & 9034 & 3409 & 5667 & 8789 & 2312 \\ 5003 & 5780 & 3098 & 679 & 4052 & 7889 & 9898 & 3234 \\ 5002 & 2012 & 1989 & 1990 & 4042 & 9163 & 7371 & 6823 \\ 9065 & 6640 & 6070 & 5460 & 3408 & 2312 & 6543 & 9656 \\ 7074 & 930 & 8074 & 7049 & 8905 & 7447 & 2323 & 5646 \\ 1877 & 5329 & 4280 & 5289 & 5034 & 6571 & 8381 & 8682 \\ 9667 & 4087 & 3287 & 676 & 5980 & 2390 & 973 & 5470 \end{bmatrix} \quad (17)$$

To obtain the optimal sensor position some of the genes in the chromosome are applied for mutation. Randomly generated mutation point is 7:

$$offs1 = \begin{bmatrix} 9081 & 4878 & 5236 & 2931 & 2330 & 3781 & 2441 & 5240 \\ 7235 & 3436 & 6543 & 7678 & 3233 & 1580 & 8083 & 1067 \\ 786 & 1012 & 1567 & 5532 & 4666 & 5040 & 3604 & 5305 \\ 7989 & 1223 & 3318 & 8582 & 8189 & 1991 & 5098 & 4590 \\ 9136 & 3267 & 4598 & 5832 & 983 & 2379 & 2442 & 3045 \\ 657 & 1777 & 1586 & 3156 & 7237 & 1098 & 7836 & 4789 \\ 578 & 3562 & 6587 & 5545 & 4555 & 1290 & 1006 & 3480 \\ 8321 & 7980 & 5062 & 4045 & 6380 & 8092 & 5890 & 4490 \end{bmatrix} \quad (18)$$

$$offs2 = \begin{bmatrix} 8846 & 4590 & 2340 & 3888 & 4302 & 1236 & 7680 & 1168 \\ 850 & 4680 & 3057 & 9034 & 3409 & 5667 & 3230 & 2312 \\ 5003 & 5780 & 3098 & 679 & 4052 & 7889 & 3035 & 3234 \\ 5002 & 2012 & 1989 & 1990 & 4042 & 9163 & 6781 & 6823 \\ 9065 & 6640 & 6070 & 5460 & 3408 & 2312 & 8060 & 9656 \\ 7074 & 930 & 8074 & 7049 & 8905 & 7447 & 6089 & 5646 \\ 1877 & 5329 & 4280 & 5289 & 5034 & 6571 & 8902 & 8682 \\ 9667 & 4087 & 3287 & 676 & 5980 & 2390 & 5670 & 5470 \end{bmatrix} \quad (19)$$

The local search of 2D Haar lifting wavelet transform (2DHLWT) decomposes the offspring 1 and offspring 2 level by level according to row-wise and column-wise and the final child 1 and child 2 are given in (20) and (21). After applying 2DHLWT, some of the values are identified as undesirable and out of the region. It shows that these values are more than $A \times A$, in this situation a simple component is applied to bring all the sensor positions into the region $P_{i,j} = abs(P_{i,j}) \bmod (A \times A)$:

$$child1 = \begin{bmatrix} 4374 & 4001 & 718 & 585 & 546 & 101 & 577 & 2108 \\ 1644 & 404 & 3027 & 3440 & 649 & 3104 & 734 & 9815 \\ 2126 & 3270 & 2557 & 4614 & 1341 & 2912 & 1799 & 596 \\ 3707 & 6992 & 2400 & 1299 & 237 & 6572 & 389 & 2209 \\ 205 & 2374 & 141 & 1402 & 255 & 2371 & 120 & 1222 \\ 4984 & 6989 & 2844 & 336 & 2486 & 7535 & 3569 & 3650 \\ 1458 & 1321 & 115 & 1029 & 671 & 776 & 2966 & 537 \\ 6080 & 3325 & 1512 & 25 & 4313 & 4977 & 2947 & 3874 \end{bmatrix} \quad (20)$$

$$child2 = \begin{bmatrix} 5030 & 213 & 1336 & 3762 & 829 & 404 & 687 & 3715 \\ 3953 & 8086 & 2931 & 4429 & 1769 & 5324 & 1653 & 5594 \\ 1466 & 1106 & 2348 & 1209 & 2001 & 4479 & 1262 & 120 \\ 1884 & 3767 & 101 & 2420 & 632 & 1284 & 3667 & 157 \\ 1506 & 4284 & 560 & 817 & 261 & 1277 & 2016 & 576 \\ 3850 & 3719 & 1796 & 415 & 5316 & 362 & 2990 & 2039 \\ 1983 & 1064 & 2593 & 801 & 353 & 1026 & 342 & 210 \\ 3274 & 9032 & 2803 & 3620 & 1617 & 5127 & 3222 & 20 \end{bmatrix} \quad (21)$$

Again, every row of the child matrix is transformed into a sensor position as described in the above process and fitness function is evaluated in Figure 7. And Qoc (%) of target coverage is achieved 81.25% of targets covered and connectivity is also achieved by 2DHLWT.

6. SIMULATION RESULTS

To evaluate the quality of the number of target coverage of the proposed method, a series of simulations were conducted in the MATLAB R2012b, Intel i7 processor, 3.4 GHz CPU, 8GB RAM, and Windows 7 environment to know the performance comparison. The simulation work is carried out with 4 to 256 sensors, and sensing ranges is varied from 125 to 225, the communication range is defined as $2R_{si}$ based on sensor sensing range; total targets are limits to 10 to 450 and region to be 100×100 , 500×500 and 1000×1000 to generate the random position of sensors. The number of initial populations is limited to 10, one-point crossover and mutation are generated randomly in the simulation. The main objectives of the proposed method are to recognize the optimal sensor position to cover entire targets so that the performance measures Qoc (%) of a different situation in fields.

Figure 7. GA+2DHLWT optimal Sensor placement

To analyze the performance of Qoc (%) of the proposed method, the simulation to be performed for random deployment (RD), a genetic algorithm-based deployment (GAD), and GA with 2DHLWT (GHLD) deployment are used. Here the Qoc (%) will depend only on fixed target positions, once the position is changing it is not possible to measure the quality of the number of targets covers. The performance of the proposed algorithm validates two different scenarios. One is the variation of targets and fixed sensing range of sensors; another is a fixed number of targets and variation of sensing ranges of sensors. The simulation environment is carried out by three different filed of $A \times A$.

Qoc is identified for 100×100 , 500×500 and 1000×1000 with different numbers of the sensor varies 4 to 256 and it depends on the number of targets, fixed sensing range $R_{si}=225$, and communication range of nodes are shown in Figure 8, 9 and 10. The average coverage of targets in RD is 60% to 70%, GAD is 70% to 80% and GHLD is 80% to 90%. Here RD and GAD placements cover a minimum number of targets while varying environment fields but the proposed algorithm GHLD covers a maximum number of targets in different fields.

The proposed method for fixed targets 400 and varying sensor ranges is 150, 175, and 200 validated in the field 1000×1000 . The average Qoc of target coverage is RD in Figure 11. Is 40% to 50%, GAD is 50% to 60% and GHLD is 70% to 85%. Whereas, the proposed method covers the maximum number of targets while changing the sensing range and communication ranges of sensors.

7. CONCLUSION

WSNs are comprised of resource-constrained nodes while facing optimal sensor placement for target coverage. This paper represents a hybrid genetic algorithm approach with 2DHLWT for identifying the optimal sensor placement to cover up the maximum number of targets with a limited number of sensors. GA efficiently formulates sensor position and it can be adjusted through the local enhancement using 2DHLWT for identifying optimized sensor position to cover up entire targets. The proposed hybrid genetic algorithm with Haar lifting has been validated by a sequence of simulation outcomes with environment regions and different scenarios. The results attained from the hybrid algorithm overcomes the existing random and genetic algorithm-based deployment in terms of coverage by

Figure 8. Qoc generated for 100×100 , $M=2N$, and $R_{si}=225$

Figure 9. Qoc generated for 500 x 500, $M=2N$, and $R_{Si}=225$

Figure 10. Qoc generated for 1000 x 1000, $M=2N$, and $R_{Si}=225$

Figure 11. Qoc generated for 1000 x 1000, and $M=400$

Sensors	Qoc (%)								
	$R_{Si}=150$			$R_{Si}=175$			$R_{Si}=200$		
	RD	GAD	GHLD	RD	GAD	GHLD	RD	GAD	GHLD
4	22	27	34	27	32	42	29	34	47
8	32	35	38	33	38	47	33	42	53
16	34	37	43	38	46	52	42	47	58
32	43	54	65	48	58	68	52	63	74
64	53	68	76	57	72	79	60	75	85

an optimal sensor position with limited sensors. In the future, aiming to study the different aspects of GA and Set K-cover problem with lifting wavelet-based sensor node deployment. The problem formation can be extended to dynamic nature with maximization of obstacle parameter in target coverage problems related to node connectivity of WSNs.

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