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ORIGINAL ARTICLE

Process of 3D wireless decentralized sensor deployment using parsing crossover scheme

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Abstract A Wireless Sensor Networks (WSN) usually consists of numerous wireless devices deployed in a region of interest, each able to collect and process environmental information and communicate with neighboring devices. It can thus be regarded as a Multi-Agent System for territorial security, where individual agents cooperate with each other to avoid duplication of effort and to exploit other agent's capacities. The problem of sensor deployment becomes non-trivial when we consider environmental factors, such as terrain elevations. Due to the fact that all sensors are homogeneous, the chromosomes that encode sensor positions are actually interchangeable, and conventional crossover schemes such as uniform crossover would cause some redundancy as well as over-concentration in certain specific geographical area. We propose a Parsing Crossover Scheme that intends to reduce redundancy and ease geographical concentration pattern in an effort to facilitate the search. The proposed parsing crossover

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method demonstrates better performances than those of uniform crossover under different terrain irregularities.

1. Introduction

In recent years, territorial security have been studied intensively for various applications such as environmental monitoring and surveillance, such as airports, public transit, emergency services or nuclear facilities. When trying to monitor large geographically distributed area, in general Wireless Sensor Networks (WSN) are deployed. A WSN usually consists of numerous wireless devices deployed in a region of interest, each able to collect and process environmental information and communicate with neighboring devices (Wang and Tseng, 2008; Bai et al., 2006; Hefeeda and Ahmadi, 2009). Hence, A WSN can be regarded as a Multi-Agent System (Wooldridge, 2002; Hewitt and Inman, 1991; Ferber, 1999; Cai et al., 2011) for territorial security, where individual agents cooperate with each other to avoid duplication of effort and to exploit other agent's capacities (Wooldridge, 2002; Athanasiadis and Mitkas, 2004; Cai et al., 2011). Sensor deployment is an essential issue in WSN, as it affects how well a region is monitored by sensors. This is a critical issue as there are a number of high potential applications for sensor deployment, such as national defense (Nickerson and Olariu, 2007), home security (Zhang, 2008), industrial surveillance (Chen, 2008) and environmental monitoring, etc. the primary objective for sensor deployment is two-fold: WSN should cover a region of interest as complete as possible, while minimizing the number of sensors deployed, and thus minimizing costs associated with sensor deployment.

Considering a region of interest monitored by sensors, one of the most critical concerns is the region coverage (Wang and Tseng, 2008; Kar and Banerjee, 2003; Zhou et al., 2007; Kumar et al., 2006; Liu and Towsley, 2004; Hefeeda and Ahmadi, 2009; Romoozi and Ebrahimpour-Komleh, 2012). In general, one of basic requirements for a WSN is that each location in a region of interest should be within the sensing range of at least one of the sensors. An alternative approach is to have a region of interest covered simultaneously by at least K sensors (Wang and Tseng, 2008; Zhou et al., 2007). Some deterministic methods have been proposed to address the problem of coverage. It has been shown that covering an area with disks of equal radius can be done in an optimal manner (Bai et al., 2006; Hefeeda and Ahmadi, 2009; Kar and Banerjee, 2003). Similar results have been reported when multiple coverage of the target area is required (Bai et al., 2006; Zhou et al., 2007; Kumar et al., 2006; Wang and Tseng, 2008). Besides, the majority of optimization methods proposed are deterministic, and are generally functions of a fixed sensing range, as shown in Fig. 1.

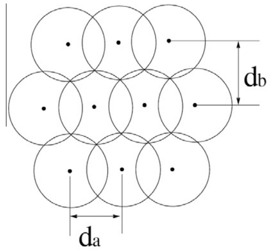

Figure 1 Pattern of the deterministic method (Bai et al., 2006; Hefeeda and Ahmadi, 2009) implemented in the paper, where $d_a = \sqrt{3}r_s, d_b = \frac{3}{2}r_s$, and r_s is the sensing range for a sensor. Circles are sensor sensing ranges, and dots are sensor positions.

The direct consequence of oversimplification in sensor deployment is that theoretically perfect coverage shown in these deterministic methods may not hold true in practice. Most sensor deployment optimization methods assume that sensors are placed on a 2D plane, without taking into account the topographic terrain information (Kar and Banerjee, 2003; Bai et al., 2006; Hefeeda and Ahmadi, 2009; Zhu et al., 2012). However, the area of interest that requires sensor deployment is rarely completely plane, usually it contains buildings and some facilities. As a result, obstacles presented in environment, such vegetation, buildings, hills or valleys are all ignored in traditional sensor deployment setting. The conventional deterministic approaches do not consider environmental factors such as terrain topology, and cannot deal with it. While WSN seems to satisfy the requirements to achieve full coverage on a target area using a deterministic method, there are no means to ensure that this coverage is truly effective in the real environment. This uncertainty of coverage thus presents a challenge in sensor deployment. To summarize, oversimplified assumptions lead to oversimplified optimization results, which cause sub-optimal WSN performance.

Nevertheless, the problem becomes non-trivial when we consider environmental factors. Given N sensors to be deployed in an area with M possible positions, the possible combination of deployment will be $\frac{M\cdot(M-1)\cdot(M-2)\cdots1}{(M-N)\cdot(M-N-1)\cdots1}$. In general, M is rather large, and this makes exhaustive search unfeasible. For example, given an area of 100 m $\times$ 100 m, even if we place a grid of 1 m and restrict sensors to be deployed only on the corner of a grid, there will be $10,000$ possible sensor positions. Considering to deploy only 10 sensors, there will be $10,000 \times 9999 \times 9998 \times 9997 \times 9996 \times 9995 \times 9994 \times 9993 \times 9992 \times 9991$ combinations, which is almost 10^{40}. Such amount is simply not easy to proceed with current computation power. The problems with such a high dimensionality cannot be solved directly, especially if the terrain exhibits some irregularities. In general, heuristic search methods such as random search can be applied, in the hope that a local optimum will emerge during the search. However, random search offers little help if high quality local optima are of a small number, because a random search of 1000 generations only explores $\frac{1}{10^{37}}$ portion of solutions in our previous example. Some more systematic search algorithms such as genetic algorithms rely strongly on some regularities or similarities of features present in best individuals (Bhondekar et al., 2009; Seo et al., 2008; Akbarzadeh et al., 2010; Brar and Virk, 2014; Karaboga et al., 2014; Tripathi et al., 2011). We have, however, little evidence that such regularities or similarities exist in a highly complex problem, and that they can be extracted in such a straightforward way. Others such as simulated annealing try to explore local information of sensors deployed, and only make short range displacement for sensors in a less frequent pace when time passes by.

In order to solve the problem, some non-deterministic search methods such as random search or simulated annealing can be applied. By taking into account terrain elevations, these non-deterministic search methods could perform better than traditional deterministic approach. In an effort to tackle the problem, some prior work based on evolutionary algorithm has been conducted (Akbarzadeh et al., 2010; Kosar and Ersoy, 2012; Akbarzadeh et al., 2013; Song et al., 2012; Gueney et al., 2012).

However, there are still some disadvantages in using conventional evolutionary approaches. Due to the fact that all sensors are homogeneous, the chromosomes that encode sensor positions are actually interchangeable, and conventional crossover schemes such as uniform crossover (Yoon and Kim, 2013; Karaboga et al., 2014; Brar and Virk, 2014; Tripathi et al., 2011; Romoozi and Ebrahimpour-Komleh, 2012) would cause some redundancy as well as over-concentration in certain specific geographical area. We notice that after a few iterations the same sensor positions or geometrically close sensor positions would be encoded in different parts in chromosome by different individuals, and the conventional crossover scheme such as uniform crossover may produce offspring with redundant or geometrically close sensors. Such a crossover is thus less effective and may delay the optimization process in sensor deployment optimization.

There are little work in sensor deployment optimization with evolutionary approaches, and most prior work conducted with such paradigms (Romoozi and Ebrahimpour-Komleh, 2012; Akbarzadeh et al., 2010; Brar and Virk, 2014; Karaboga et al., 2014; Tripathi et al., 2011) simply used evolutionary algorithms as a black box approach without taking into account the problem of homogeneous gene representation. Hence, we propose a Parsing Crossover Scheme that reduces redundancy and eases geographical concentration pattern to facilitate the search. The proposed parsing crossover method demonstrates better performances than those of uniform crossover under different terrain irregularities.

The remainder of the paper is organized as follows. The problem statement is presented in the next section, followed by a presentation of the proposed method. The experimental protocol and results are then summarized, concluding the paper with discussions and perspectives.

2. Problem statement

Although there are some common notions on critical issues such as coverage (Ahmed et al., 2005; Boukerche and Fei, 2007; Kumar et al., 2006; Zhou et al., 2007), there are few comprehensive frameworks that have been done for sensor deployment optimization. In most cases, sensor deployment optimization is regarded as an overly complex problem, thus generic heuristic algorithms are often used for the optimization task (Bhondekar et al., 2009; Seo et al., 2008). A more comprehensive framework was proposed in Akbarzadeh et al. (2010). Still, we believe that are some important concepts that are yet to be clearly defined or outlined.

Given a sensor $\mathbf{s_i}$ with a sensing range d_r and a point of interest $\mathbf{p_j}$ with a distance d_{ps} away from sensor $\mathbf{s_i}$, we first define the visibility $v(\mathbf{s_i}, \mathbf{p_j})$ as 1 if the point $\mathbf{p_j}$ is visible to sensor $\mathbf{s_i}$, and as 0 otherwise. Once the visibility is defined, the coverage of the sensor $\mathbf{s_i}$ to the point $\mathbf{p_j}$ can be calculated (Ko et al., 2011):

Definition 1 (*Single Sensor Binary Coverage on a Point*). The sensor binary coverage $c(\mathbf{s_i}, \mathbf{p_j})$ of a sensor $\mathbf{s_i}$ with detection range d_r on the point $\mathbf{p_j}$ can be defined as:

$$c(\mathbf{s_i}, \mathbf{p_j}) = 1, \ \textit{if} \ \max\ (0, d_r - d_{ps}) \cdot v(\mathbf{s_i}, \mathbf{p_j}) > 0 \tag{1}$$

$$c(\mathbf{s_i}, \mathbf{p_j}) = 0, \ \textit{otherwise} \tag{2}$$

Alternatively, we can extend the definition of $c(\mathbf{s_i}, \mathbf{p_j})$ into a probability setting:

Definition 2 (*Single Sensor Probability Coverage on a Point*).

$$c(\mathbf{s_i}, \mathbf{p_j}) = f(d_{ps}) \cdot v(\mathbf{s_i}, \mathbf{p_j}) \tag{3}$$

where $f(d_{ps})$ is a probabilistic sensor detection function, the exact function depends on sensor behavior model. For example, a sigmoid detection function can be used if justified:

$$f(d_{ps}) = \frac{1}{1 + \exp\left[-\left(\frac{\alpha}{d_{ps}} - \beta\right)\right]} \tag{4}$$

where α and β are parameters that define exact sensor detection behaviors. A point of interest is regarded as covered if it is covered by at least of sensors deployed. If there are N sensors deployed, instead of just one single sensor, then the coverage of a point $\mathbf{p_j}$ can be defined as (Ko et al., 2011):

Definition 3 (*Binary Coverage on a Point*). The binary coverage $c(\mathbf{p_j})$ on a point $\mathbf{p_j}$ can be defined as:

$$c(\mathbf{p_j}) = 1, \; if \sum_{i=1}^{N} c(\mathbf{s_i}, \mathbf{p_j}) > 0 \tag{5}$$

$$c(\mathbf{p_j}) = 0, \; otherwise \tag{6}$$

where $\mathbf{s_i}$ denote a sensor among total N sensors, $1 \leqslant i \leqslant N$. Again, a probabilistic coverage on a point can be implemented if sensor behavior is known:

Definition 4 (*Probabilistic Coverage on a Point*). The probabilistic coverage $c(\mathbf{p_j})$ on a point $\mathbf{p_j}$ can be defined as (Ko et al., 2011):

$$c(\mathbf{p_j}) = 1 - \prod_{i=1,\dots,N} \left(1 - c(\mathbf{s_i}, \mathbf{p_j})\right) \tag{7}$$

Note that $c(\mathbf{s_i}, \mathbf{p_j})$ is the single sensor $\mathbf{s_i}$ probability coverage on a point $\mathbf{p_j}$.

With the knowledge of the coverage between sensor $\mathbf{s_i}$ and all points of interest, the overall coverage by sensor $\mathbf{s_i}$ can be define by aggregation. If there are m points of interest, then the coverage by a sensor $\mathbf{s_i}$ can be defined as:

Definition 5 (*Coverage by a Sensor*). The coverage $c(\mathbf{s_i})$ by a sensor $\mathbf{s_i}$ can be defined as (Ko et al., 2011):

$$c(\mathbf{s_i}) = \sum_{j=1}^{m} c(\mathbf{s_i}, \mathbf{p_j}), 1 \leqslant j \leqslant m \tag{8}$$

where $\mathbf{p_j}$ is a point, $1 \leqslant j \leqslant m$, in a region of interest R. This definition applies for both binary and probabilistic coverages. Given N sensors to be deployed in a terrain, and m points in a region of interest, the global coverage $c(S)$ can be defined as the sum of coverage of all points of interest, which in turns is a function of all sensors deployed, $\{\mathbf{s}_1, \mathbf{s}_2, \dots, \mathbf{s}_N\}$:

Definition 6 (*Global Coverage*).

$$c(S) = \sum_{j=1}^{m} c(\mathbf{p_j}), \forall j, p_j \in R \tag{9}$$

where $\mathbf{p_j}$ is a point, $1 \leqslant j \leqslant m$, in a region of interest R. Again, the same definition works for under both binary and probabilistic coverage settings. Apparently, the global coverage $c(S)$ is a function of terrain elevations $p_{j,z}$, $1 \leqslant j \leqslant m$ of all points of interest in region R and sensor positions $s_{i,x}, s_{i,y}$ and sensor elevations $s_{i,z}$, $1 \leqslant i \leqslant N$. For simplicity, we denote the series of $p_{j,z}$ as $\mathbf{p_{j,z}}$ and the sensor positions and elevations as $\mathbf{s_{i,x}}, \mathbf{s_{i,y}}, \mathbf{s_{i,z}}$, respectively:

$$c(S) = \Phi(\mathbf{p_{j,z}}, \mathbf{s_{i,x}}, \mathbf{s_{i,y}}, \mathbf{s_{i,z}}) \tag{10}$$

Thus, the goal for sensor deployment is to position sensors in a way that global coverage is maximized:

$$\{\mathbf{s_{i,x}}, \mathbf{s_{i,y}}\} = \arg\max \Phi(\mathbf{p_{j,z}}, \mathbf{s_{i,x}}, \mathbf{s_{i,y}}, \mathbf{s_{i,z}}) = \arg\max c(S) \tag{11}$$

Note that $\mathbf{p_{j,z}}$ and $\mathbf{s_{i,z}}$ are terrain effects and the system has no controls on these factors.

Here we notice that we derive global coverage $c(S)$ not by sensors, but by points in a region interest. The reason is that it is far less costly to take into account multiple coverage effects by points of interest rather than by sensors. We simply cannot know the extent to which a sensor has duplicated coverage with other sensors unless we examine all points of interest that may potentially be covered. This causes some problems in optimization, because we cannot simply add up coverage from all sensors to obtain global coverage. Thus, we cannot regard the problem as individual optimization problems, because optimization of individual sensor coverage would not be equal to the overall global coverage. Moreover, because the sum of coverage of all sensors does not equal to global coverage, we cannot evaluate the fitness of an individual sensor only based on its coverage achieved.

Given the high dynamic nature of the problem, it is quite costly to predict the behaviors of other agents and the consequences of these behaviors in such a complex and dynamic setting. Due to the intrinsic complexity of the problem, advanced evolutionary approaches would perform better than traditional heuristic search. However, since all sensors are homogeneous, the chromosomes that code sensor positions are actually interchangeable, and conventional crossover schemes such as uniform crossover would cause some redundancy as well as over-concentration in certain specific geographical area. We thus propose in the next section our parsing crossover method.

3. Proposed method

Given N sensors, each sensor position can be encoded by its x coordinate and y coordinate, hence the sensor deployment needs $2 \cdot N$ sensors to depict sensor positions. Each sensor position is thus represented by a gene-pair in chromosome.

The conventional crossover scheme may encode identical sensors into different genes, and this may cause two problems: (a) offspring may have redundant sensor positions in its chromosome; (b) offspring may not inherit the gene-pairs that both parents have.

We are mainly motivated by three purposes to propose this parsing crossover method for sensor deployment : (a) make sure that offspring would not have redundant gene-pairs; (b) if both parents have a certain gene-pair, then make sure that their offspring would inherit it; (c) under the condition that both (a) and (b) are satisfied, make sure that more distant sensor positions, i.e., sensor positions that are less similar to existent sensor positions, have higher chance to be inherited.

In order to satisfy these purposes, the parsing crossover method can be carried out by the following algorithm:

Algorithm 1. Pseudo-code of parsing crossover scheme.

Given two parents, each parent encodes N sensor positions, and contains $2 \times N$ genes:
1. Merge chromosomes from both parents into a new chromosome, as group A with $2 \times N$ gene-pairs, or $4 \times N$ genes,
2. Separate all $2 \times N$ gene-pairs from group A into two groups: group B with N_b redundant gene-pairs and group C with N_c unique gene-pairs,
3. Prase redundant gene-pairs in group A such that all duplicated gene-pairs would be eliminated, and all left-over gene-pairs are unique
4. Calculate distances d_i of all gene-pairs $(g_{i,x}, g_{i,y})$ in group B with all gene-pairs in group A,

$$d_i = \sum_{k=1}^{2N} \sqrt{(g_{i,x} - g_{k,x})^2 + (g_{i,y} - g_{k,y})^2}$$

5. Normalize distances d_i of all gene-pairs $(g_{i,x}, g_{i,y})$ to obtain the selection probability p_i,

$$p_i = \frac{d_i}{\sum_{i=1}^{N_b} d_i}$$

6. Add all N_b gene-pairs from group B into a new group D
7. Select $N - N_b$ gene-pairs from group C into group D; the probability of a gene-pair $(g_{i,x}, g_{i,y})$ in group c to be selected is exactly its normalized distance p_i
8. Return group D as final result of crossover.

4. Simulations

In order to verify the validity of the proposed method, we carried out a number of experiments on terrains with different irregularities. Note that we are simply unable to test all terrain types for two reasons: (a) Millions of types of terrain exist, and even categorization may not be feasible; (b) currently there is simply no measure on terrain irregularities and we cannot quantify it given any terrain. Hence, we work another way around, first we define a standard deviation of terrain elevation as irregularity, and then we generate artificial terrains using different standard deviation and test different search algorithms.

4.1. Experimental protocol

We deploy 8 sensors in an area with size 100 m $\times$ 100 m, thus the problem has the complexity of $10,000 \times 9999 \times 9998 \times 9997 \times 9996 \times 9995 \times 9994 \times 9993$ combinations, which is almost 10^{32}. The coverage is based on binary setting, and each sensor is supposed to have a radius of 30 m of detection range. Sensors are deployed one meter high above the ground, so there is an asymmetry between detecting positions and detected positions. Consequently, we assume that any point of interest is detectable under the condition that it is inside the detection range of a sensor and that there is no obstruction on the line of sight between the sensor and the point.

Note that a real world WSN sensor has more complex behaviors and many more factors to take into account, such as a "dipole" pattern, battery issues, communication routes, etc. Nevertheless, we regard the 3D obstruction as one of the most relevant ones. In this paper, we simply try to stress the importance of terrain issues in considering WSN coverage, and do not deal with all of them at the same time.

Terrain has various elevation variations, the elevation variations are in Gaussian distribution with standard deviation from 0.1 m to 1200 m and a mean of 0. Terrain is almost flat with only 0.1 m of standard deviation, but can be quite complex with 1200 m of standard deviation.

To introduce asymmetry in the experiment, sensors would be placed one meter above the ground instead of on the ground. We tested several methods, including traditional deterministic pattern (Bai et al., 2006; Hefeeda and Ahmadi, 2009), Random Search, Simulated Annealing, Genetic Algorithm with uniform crossover, one point crossover, two point crossover, and the proposed parsing crossover.

Each method makes 500 displacement iterations in a test, with 30 tests in total, except for traditional deterministic pattern, and genetic algorithm. For genetic algorithm, we set up a population of 10 individuals, hence there would be 10 displacement evaluations in each generation. Thus, genetic algorithm only contains $\frac{500}{10} = 50$ generations to be comparable with other methods. Crossover rate is 0.9 for uniform crossover. Mutation rate is 0.05, and the disturbance in case of a mutation is a Gaussian distribution with standard deviation $\sigma_r = 10$ m. For simulated annealing, we set $\alpha = \frac{1}{3}$ and $\beta = \frac{1}{2}$ for temperature function, and $\sigma_r = 10$ m for displacement distance, the same as in genetic algorithm.

4.2. Experimental results

Table 1 shows experimental results. Traditional deterministic deployment pattern has the lowest coverage among all methods tested. This is not surprising given that traditional deterministic deployment does not consider terrain elevations.

Among purely heuristic methods, we notice that simulated annealing with displacement of only one sensor at a time generally performs better than random search. On contrary, simulated annealing with displacement of all sensors at the same time in general does not perform as well as random search. It may suggest that simulated annealing can perform better than random search, but only if we displace one sensor at a time rather than displace all sensors at the same time. A plausible explanation is that if we displace only one sensor at a time, the rest of sensors preserve more or less the structure of the network. Thus, during the search simulated annealing would explore a better solution for a given network, of which properties are somehow stable. However, if we displace all sensors at the same time, simulated annealing may actually generate a completely different network. A complete new network may prevent simulated annealing from making

Table 1 Coverage percentage on the target areas for sensor deployment. 8 sensors in total are deployed in an area with size 100 m × 100 m, each sensor has a radius of 30 m of detection range, and all sensors are placed one meter above the ground. The coverage is based on binary setting. Terrain has various elevation variations, the elevation variations are in Gaussian distribution with standard deviations from 0.1 m to 1200 m. Sensors are deployed one meter high above the ground. Each method makes 500 iterations in each test with 30 tests in total, except for traditional deterministic deployment and Genetic Algorithm. The mean and the standard deviation of these 30 tests are shown. Std denotes for standard deviation.

Method random terrain elevation (m of std)	Random simulated search (%)	Simulated annealing all at a time (%)	Simulated genetic annealing one at a time (%)	Genetic algorithm with uniform crossover (%)	Genetic algorithm one point crossover (%)	Genetic algorithm two point crossover (%)	Genetic algorithm with parsing crossover (%)
0.1	75.58	75.04	76.63	77.62	79.25	78.97	76.70
0.2	59.39	58.70	60.94	62.97	65.26	64.96	62.98
0.3	51.65	50.41	52.94	56.36	57.97	58.22	56.87
0.4	45.91	45.18	48.05	51.82	54.31	54.49	53.84
0.5	41.92	40.95	44.45	48.55	50.77	51.21	51.08
0.6	39.17	38.00	41.57	46.66	48.54	49.54	49.01
0.7	37.21	35.82	38.91	44.96	47.19	47.68	48.28
0.8	35.83	33.95	37.60	43.83	46.73	46.77	47.40
0.9	34.47	32.96	35.93	43.39	45.21	45.33	46.12
1.0	33.00	32.05	35.78	41.69	44.06	44.48	45.30
1.1	32.29	31.15	34.32	40.60	43.93	43.61	44.71
1.2	31.29	30.05	33.07	40.95	43.23	44.14	44.76
2.4	27.69	26.65	30.47	41.40	42.48	42.77	43.34
4.8	25.54	24.49	28.32	39.83	40.54	40.96	41.15
6	25.53	24.44	27.81	41.04	40.67	40.64	41.72
12	24.81	22.83	27.31	39.21	39.67	39.94	40.45
24	23.41	23.11	26.65	39.95	40.09	40.46	40.82
48	23.42	23.10	26.04	37.86	38.91	39.28	39.63
60	23.86	22.35	26.12	37.83	38.64	38.74	39.14
120	23.37	22.07	25.39	38.74	39.43	39.79	40.21
240	22.85	22.51	27.03	39.83	40.19	39.42	40.89
480	23.41	22.45	26.17	38.61	38.92	39.02	39.33
600	23.23	22.46	26.52	39.32	39.29	39.96	40.05
1200	23.42	22.33	26.31	39.53	39.66	40.03	40.15

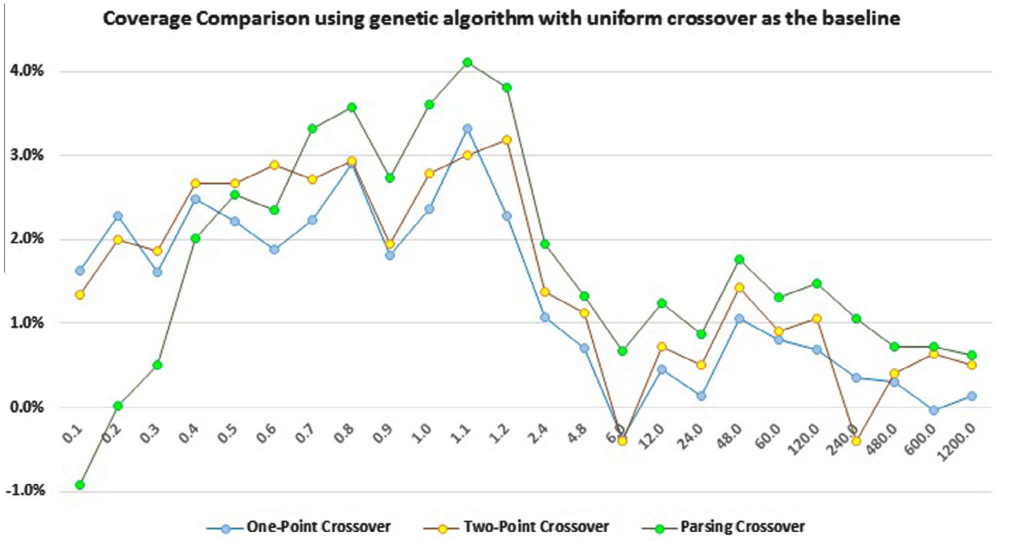

Figure 2 Genetic Algorithm crossover scheme performance comparison using uniform crossover as the benchmark: the evaluation was carried out on different terrain complexities with elevation standard deviation from 0.1 m to 1200 m. Genetic Algorithm with uniform crossover is set as the benchmark as thus has always the value 0; we compare its performance with those of one-point crossover, two-point crossover and the proposed parsing crossover.

use of properties of a stable network. As there are some constraints on displacement distance, simulated annealing with displacement of all sensors at the same time may not be as good as random search.

Genetic algorithm apparently performs better than both simulated annealing approaches. Also, genetic algorithm has the best performance when the terrain irregularity is low. Among different crossover schemes, we observe that uniform crossover is consistently outperformed by all other crossover schemes, as shown in Fig. 2. For terrain with low variations, one point crossover tends to outperform other crossover schemes. However, as terrain starts to show medium irregularity, two point crossover seems to have the best performance. Furthermore, the proposed parsing crossover scheme has the best performance when the terrain becomes even more irregular.

5. Discussion and conclusion

Sensor deployment in a 3D environment is a non-trivial task, as it is basically a NP-hard non-convex optimization problem. In order to solve the problem, non-deterministic optimization methods such as random search, simulated annealing or evolutionary algorithm (Akbarzadeh et al., 2010) can be applied. By taking into account terrain elevations, these non-deterministic optimization methods could perform better than traditional deterministic approach.

However, due to the fact that all sensors are homogeneous, the evolutionary algorithm will encounter some problems. The chromosomes that encode sensor positions are actually interchangeable, and conventional crossover schemes such as uniform crossover would cause some redundancy as well as over-concentration in certain specific geographical area. We notice that after a few iterations the same sensor positions or geometrically close sensor positions would be encoded in different parts in chromosome by different individuals, and the conventional crossover scheme such as uniform crossover may produce offspring with redundant or geometrically close sensors. Such a crossover is thus less effective and may delay the optimization process in sensor deployment optimization.

Hence, we proposed a parsing crossover scheme for genetic algorithm. The experimental simulation confirms that the proposed crossover scheme performs better than traditional uniform crossover, one-point crossover and two-point crossover schemes. However, although the proposed scheme outperforms all other compared methodologies in highly irregular terrain, we acknowledge that there may still be some room to further improve the crossover scheme and to make it more robust regardless of irregularity in optimization space.

Despite the fact that the proposed method does perform better than most conventional schemes, our parsing crossover relies on the mechanism of genetic algorithm - a population-based optimization. Hence, in circumstances where genetic algorithm fails, we are uncertain whether our parsing crossover scheme can be a full remedy. In our simulation, we do not observe any instances of general genetic algorithm failure. However, this is an issue that we may need to pay more attention in the future.

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