Configuration of Sensors on a 3-D Terrain: An Approach Based on Evolutionary Multi-objective Optimization

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ABSTRACT

The article deals with the problem of deployment and configuration of a given set of sensors on a synthetically generated 3-D terrain using evolutionary computation. It proposes a multi-objective formulation of this problem which aims at positioning and utilizing sensors in such a way that several conflicting objectives of our interest are optimized simultaneously and then this optimization problem is solved using a recent fuzzy dominance based decomposition technique for multi-objective optimization called MOEA/DFD. Simulation results not only validate the efficiency of multi-objective approach over single-objective approach solved with a Differential Evolution (DE) algorithm, but also justify the superiority of MOEA/DFD over the original MOEA/D-DE and another very well-known MO algorithm called NSGA-II (Non-dominated Sorting Genetic Algorithm).

Categories and Subject Descriptors:

I.2.9. [Artificial Intelligence]: Robotics --- *Sensors*; J.1. [Computer Applications]: Computers In Other Systems --- *Military*; G.1.6 [Numerical Analysis]: Optimization— *Unconstrained optimization*

General Terms:

Algorithms, theory, experimentation

Keywords

Wireless sensor networks, 3-D terrain, sensor attributes, sensor planning, multi-objective optimization.

1. INTRODUCTION

In our work, here we develop and present a framework that has a novel approach for determining the configuration of sensors, along with locating and setting their orientational sensor-specific parameters on a synthetically generated 3-D terrain with multiple objectives[1]. This paper presents a new multi-objective approach for deploying and configuring multiple sensors on a 3-D terrain by considering our MOEA/DFD algorithm-based framework. Our solution approach relies on the rational trade-off between three conflicting objectives that maximize the coverage area while maintaining the maximum stealth, and minimize the total acquisition cost of deploying the sensors.

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2. MOEA/DFD

Though decomposition is an effective process for maintaining convergence and diversity simultaneously for an MOP, still there are few drawbacks in this method. Each of the weight vectors associated with an individual in the population tries to select a new offspring whose position in the objective function hyper space is farther away from the parent individual and hence in this process diversity is maintained. But in course of this process, the weight vector having affinity towards the offspring at a further position in the function space with respect to the parent individual, will neglect those offspring which may be potentially better but lying closer in comparison to that parent individual. To circumnavigate this issue, we have introduced MOEAD/DFD [2] which employs a fuzzy Pareto dominance concept to compare two solutions and uses the scalar decomposition method only when one of the solutions fails to dominate the other in terms of a fuzzy dominance level [3]. The reason is two-fold: Firstly, the basic definition of dominance does not make a difference between two solutions when neither is dominating, and secondly, it measures the extent by which one solution dominates the other.

3. EXPERIMENTAL RESULTS

3.1 Experimental Setup

First we have generated synthetic terrains and covered these terrains with natural and/or artificial objects and weather conditions using the Hill algorithm considering the terrain to be a square of length 2.56 km; hence the area of the terrain is 6.5536 sq. km. Now for sensor deployment, we divide the entire terrain into 16 squares of equal size. So, the squares (polygons, as mentioned earlier) are of area 0.4096 sq. km, or of length 0.64 km. Now one sensor is assigned to each polygon and placed in the center-of-mass of the corresponding polygon.

Among the various attributes of the sensors, we have considered the heading angle, θ_i and the tilt angle, σ_i to be decision variables of the optimization problem and assigned certain values to rest of them. Since it is a 16 sensor-node setup, the problem becomes a 32 dimensional optimization problem.

Table 1. Different types of sensors and specifications

Type T_i	Δ_i (in metres)	α_i (in degree)	$\beta_L = \beta_U$ (in degree)	CostF$_i$
A	880-1280	120-180	0-30	200
B	480-880	60-120	30-60	100
C	80-480	0-60	60-90	50

Now there are three types of sensors, which are categorized on the basis of its behavioral attributes. They are specified in Table 1. Other parameters of the sensor networks are described below:

- Length of the entire terrain= 2.56 km;
- Length of the polygon=0.64 km;
- Number of sensor nodes employed= 16;

3.2 Results

Along with presenting results of other MO algorithms, we have also compared the performance with that of two well-known single-objective algorithms. In single objective approaches using DE and PSO, some problem-specific weight-values are taken and one single-objective is formed using those values, which is optimized using the single-objective algorithms.

For multi-objective algorithms (NSGAII, MOEA/D, and MOEA/DFD), a decision maker rule is employed to aggregate the three objectives using some weight-values which are kept same as those used in single-objective approaches given as follows:

$$f_{obj} = \max\{w_1 f_1(\overrightarrow{x^i}) + w_2 f_2(\overrightarrow{x^i}) + w_3 f_3(\overrightarrow{x^i})\} \ \forall i = 1:N' \quad (1)$$

where, $\overrightarrow{x^i}$ signifies the i-th solution vector, N' signifies the number of Pareto optimal solutions and if it is maximum for $k = i$, then the k-th solution $\overrightarrow{x^k}$ is picked as the final decision variable. f_1, f_2, and f_3 are the three objectives i.e. visibility, stealth and cost-effectiveness.

Table 2. Aggregated objective-values for different algorithms

Objective-weights \ Algorithms	DE	PSO	NSGAII	MOEA/D	MOEA/DFD
[0.2, 0.2, 0.6]	0.442	0.424	0.564	**0.746**	0.675
[0.2, 0.6, 0.2]	0.418	0.432	0.655	0.682	**0.753**
[0.6, 0.2, 0.2]	0.245	0.223	0.351	0.765	**0.993**
[0.4, 0.3, 0.3]	0.886	0.809	0.763	0.778	**0.976**

In our study, we have conducted the comparison by taking 4 sets of weight-values as given in Table 2. The first three sets assign a higher value to one objective and lower values to the rest, whereas the last set assigns almost equal values to all the objectives.

As we can see from C-metric values given in Table 3, and Pareto front figure given as Fig. 2 that MOEA/DFD outperforms NSGAII and MOEA/D in all the cases. The spacing measures shown in Table 4 also suggest that the distribution of the approximated Pareto front is best for MOEA/DFD. Thus from the multi-objective point of view MOEA/DFD performs the best.

Table 3. Coverage Metric measure for MOEA/DFD (A), MOEA/D (B) and NSGAII(C)

$C(A, B)$	$C(B, A)$	$C(A, C)$	$C(C, A)$
0.3464	0.0981	0.6432	0.0506

Table 4: Spacing Metric for MOEA/DFD, MOEA/D and NSGAII

MOEA/DFD	MOEA/D	NSGAII
0.00342	0.00745	0.0129

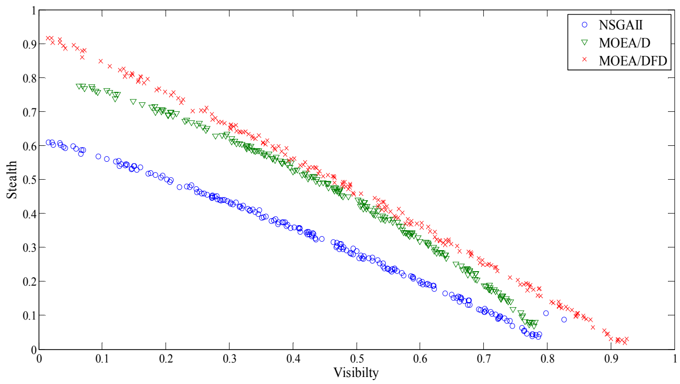

Figure 1. Pareto fronts of Visibility and Stealth

4. CONCLUSION

We have conducted an experimental study on a synthetic 3-D terrain with various characteristics. The results of experiments clearly point out the effectiveness and robustness of our MOEA/DFD-based solution under all values of several algorithms and problem-specific parameters.

5. REFERENCES

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