Elite Adaptive Particle Swarm Optimization for Target Coverage Problem in High-density Wireless Sensor Networks

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Abstract. The rapid development of intelligent sensing, micro electro-mechanical systems and communication has made it feasible to equip low computational complexity, low energy consumption, autonomous, and intelligent sensor nodes. High-density wireless sensor networks (HDWSNs) have information acquisition and communication abilities. HDWSNs are widely used in a number of areas including traffic avoidance, homeland security, target monitoring and so on. One of the major challenges in HDWSNs is to maximize the point coverage percentage. It is important since it is known that obtaining an optimal coverage target for HDWSNs is an NP-hard problem. In this paper, we use an elite adaptive particle swarm optimization (EAPSO) to solve the issue of target coverage in HDWSNs. In order to improve the effectiveness of system, a system model is provided to evaluate the monitored rate for HDWSNs. The proposed EAPSO with an efficient particle swarm optimization in discrete mode has the advantages of both adaptive as well as elite strategy. Numerical simulations are conducted with a number of nodes and targets using EAPSO, evolutionary algorithm (EA) and simulated annealing (SA). In the simulations, a better performance of EAPSO is given when it is compared with EA and SA with the same computational complexity.

Keywords. Wireless sensor networks, Particle swarm optimization, Target coverage

1. Introduction

The advance of data gathering, hardware manufacturing and networking technologies have improved the wireless sensor networks [1]-[4]. High-density wireless sensor networks (HDWSNs) have numerous sensing devices, which have many abilities, such as limited communication, computation, information acquisition, and free-infrastructure [5]. HDWSNs are a group of dense devices with limited sensing capabilities. Each sensing unit is made up of the following systems, which includes the computing system, the small power source system, the short-range radio transmitter system as well as the environmental monitoring system. HDWSNs have been widely designed in the domains of traffic control, environment surveillance, smart home, industry and many other areas [6].

Recently target coverage has been receiving a lot of attention for wide applications of HDWSNs. The target coverage scheme is usually used for HDWSNs to enhance the target coverage rate [7]. Enhancing the target coverage efficiency is an NP-hard problem [8]. Although the exhaustive search can achieve better coverage efficiency compared with other schemes, the computational difficulty is large for practical implementations [9].
Many heuristic algorithms have been proposed to solve the target coverage problem. In [10], a target coverage approach to maximize the target coverage rate in WSNs is investigated using evolutionary algorithm (EA). The EA has shown great performance when it comes to total system sensing range and the target coverage rate. While the EA produces some convergence troubles. In [11] a simulated annealing (SA) scheme is presented to investigate the target coverage rate in HDWSNs. This work focused on optimizing the total system sensing range with network constraints. However, in practice SA suffer from a low convergence rate.

In this paper, we propose an elite adaptive particle swarm optimization (EAPSO), a randomized swarm optimization algorithm for target coverage in HDWSNs, motivated by adaptive theory and elite theory. It is more powerful and simpler than available heuristics, and can avoid local optima while searching for a better result. The simulation results display that the EAPSO method provides a large amount of successfully monitored targets over the current EA and SA methods.

2. System Model
The system model is given to deal with the issue of the target coverage when the monitoring capabilities and sensing radius is limited. Supposed that there are $X$ targets and $Y$ sensor nodes in the monitored areas. The coverage relationship could be represented by a matrix $A$ in (1):

$$A = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,Y-1} & a_{1,Y} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,Y-1} & a_{2,Y} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ a_{X-1,1} & a_{X-1,2} & \cdots & a_{X-1,Y-1} & a_{X-1,Y} \\ a_{X,1} & a_{X,2} & \cdots & a_{X,Y-1} & a_{X,Y} \end{bmatrix} (a_{x,y} \in \{0,1\})$$ (1)

In (1), the matrix represents the link among the $y_{th}$ node as well as the $x_{th}$ target, and $a_{x,y} = 1$ suggests the $x_{th}$ target in the sensing range of the $y_{th}$ node. $a_{x,y} = 0$ means that the target is not within the coverage of the sensor.

In equation (2), $B$ represents the monitoring relationship matrix.

$$B = \begin{bmatrix} b_{1,1} & b_{1,2} & \cdots & b_{1,Y-1} & b_{1,Y} \\ b_{2,1} & b_{2,2} & \cdots & b_{2,Y-1} & b_{2,Y} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ b_{X-1,1} & b_{X-1,2} & \cdots & b_{X-1,Y-1} & b_{X-1,Y} \\ b_{X,1} & b_{X,2} & \cdots & b_{X,Y-1} & b_{X,Y} \end{bmatrix} (b_{x,y} \in \{0,1\})$$ (2)

In (2), $b_{x,y} = 1$ means weather the $x_{th}$ objective can be allocated by the $y_{th}$ sensor. If $b_{x,y} = 0$, the $x_{th}$ objective locates in the sensing region of the $y_{th}$ node, nevertheless, it cannot be monitored, otherwise, the $x_{th}$ objective isn't in the sensing region of the $y_{th}$ node.

If $V$ targets can be monitored by each node within the coverage simultaneously, the constraint can be demonstrated in (3).

$$\sum_{x=1}^{X} b_{x,y} \leq V (y = 1, \cdots, Y)$$ (3)

It is assumed that every objective must be monitored by no less than $W$ sensors. Every sensor can detect no more than $V$ targets at the same time. When the optimization is to increase the quantity of monitored targets, then, the fitness function in this paper to calculate the number of targets can be shown in (4).
\[ \max f(b_{1,1}, b_{1,2}, \ldots, b_{X,Y}) = \sum_{x=1}^{X} c_x \]  \hspace{1cm} (4)

Where
\[ c_x = \begin{cases} 
1 & \sum_{y=1}^{Y} b_{x,y} \geq W \\
0 & \sum_{y=1}^{Y} b_{x,y} < W 
\end{cases} \]  \hspace{1cm} (5)

Subjected to (3) and (6)
\[ b_{x,y} \leq a_{x,y} \]  \hspace{1cm} (6)

(3) means that every sensor can only detect a few objectives, while (6) means that only targets within the sensor coverage area can be monitored by the sensor. In (5), \( c_x = 1 \) means that the \( x_{th} \) objective will be monitored; conversely, it will not be noticed.

3. An elite adaptive particle swarm optimization for target coverage problem in HDWSNs

Particle swarm optimization (PSO) is a swarm strategy, where each particle in this algorithm represents a solution. In this paper, the adaptive and elite strategies are employed to create a more effective binary particle swarm optimization. The main steps of EAPSO can be described as following.

3.1. Population Encoding

In EAPSO, suppose that there are \( X \) particles in the population. The EAPSO can be encoded as shown in (7), and only the matrix \( A \) with value of 1 is encoded:
\[
A = \begin{bmatrix}
0 & 1 & 0 & 0 & 0 \\
1 & 0 & 1 & 0 & 1 \\
0 & 0 & 1 & 0 & 1 \\
1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 1 \\
\end{bmatrix}
\quad B = \begin{bmatrix}
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 \\
0 & 0 & 1 & 0 & 1 \\
1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
\end{bmatrix}
\]  \hspace{1cm} (7)

3.2. Initialization

Each row of population in the EAPSO represents a particle. The algorithm is discussed in the following description: In a \( Y \)-dimensional space, assuming there are \( X \) particles. \( X \) should be set according to the target coverage problem. The population can be represented as \( B = \{ b_1, b_2, \ldots, b_X \} \), and \( b_x = \{ b_{x,1}, b_{x,2}, \ldots, b_{x,Y} \} \) represents the current target in the \( Y \)-dimensional search area.

3.3. Fitness Function

The optimization scheme to improve the coverage rate can be shown in formula (4).

3.4. Update speed and position

Suppose that \( S \) is the current speed of the particle, \( S = \{ s_1, s_2, \ldots, s_X \} \), \( f = \{ f_1, f_2, \ldots, f_X \} \), \( x = \{ 1, 2, \ldots, X \} \). \( f_x \) represents the position of particle, which can be also regarded as the number of successfully monitored targets of the \( x_{th} \) particle. The best position it has experienced is recorded as \( l = \{ l_1, l_2, \ldots, l_x \} \). \( f_g \) is the largest number of successfully monitored targets of the population,
which is an elite particle selected from \( f_x \). The elite particles have advantage to improve the convergence speed. By constantly looking for \( f_x \) and \( f_g \) of particles, their speed and position is constantly updated through the following formula:

\[
\begin{align*}
    s_x(t+1) &= ws_x(t) + z_1d_1(l_x(t) - f_x(t)) + z_2d_2(f_g(t) - f_x(t)) \\
    f_x(t+1) &= f_x(t) + s_x(t+1)
\end{align*}
\] (8)

where \( y = \{1, 2, \ldots, Y\} \). \( w \) is inertia weight coefficient. \( t \) represents iteration times; \( z_1 \) and \( z_2 \) are two constants, which mean the learning factor. This paper sets \( z_1 = z_2 \), so that the individuals have the same global and local search capabilities. \( d_1 \) as well as \( d_2 \) represent the random value between 0 and 1. The value of \( s_x \) is usually taken \( s_x \in [-s_{\text{max}}, s_{\text{max}}] \), which is to ensure that particles are in the search area as much as possible during the evolution process.

In general, the monitoring relationship matrix is updated by a sigmoid mapping method, and the sigmoid function is as follows:

\[
g(s_x) = \frac{1}{1 + e^{-s_x}}
\] (10)

\[
b_{xy} = \begin{cases} 
1 & \text{if } \text{rand} \leq g(s_x) \\
0 & \text{otherwise} 
\end{cases}
\] (11)

In (10) and (11), \( \text{rand} \) is a random number between 0 and 1. \( g(s_x) \) indicates the probability that \( b_{xy} \) is 1.

3.5. Termination Condition
The algorithm will be executed until the maximum iteration is reached.

3.6. Elite Operator
In EAPSO, we introduce the elite strategy, and complete the elite selection operation according to the number of successfully monitored targets. In the elite selection operation, the population is arranged in descending order, and then the optimal individuals are retained to form a new population and inherited to the next generation. In the EAPSO, the elite operation does not reduce the number of successfully monitored targets, which reduces the probability that the algorithm falls into local optimum.

3.7. Adaptive Operator
In EAPSO, the larger \( w \) is beneficial to the global search, and the smaller \( w \) is helpful to accelerate the convergence of the algorithm. The adaptive operator is used to adjust the value of \( w \) to improve the performance of the algorithm.

\[
w(t+1) = \begin{cases} 
    w(t)_{\text{max}} \times u & f_x \geq f_{\text{avg}} \\
    w(t)_{\text{min}} \times u & f_x < f_{\text{avg}} 
\end{cases}
\] (12)

Where \( f_{\text{avg}} \) means the average number of successfully targets of the population, \( w(t)_{\text{max}} \) as well as \( w(t)_{\text{min}} \) is the best and lowest of the inertia weight coefficient. \( u \) means a constant, which takes 1.05. When \( f_x \) is greater than the average fitness, \( w \) is larger, the EAPSO prefers a wider range of search. Otherwise, the EAPSO prefers local search, which is good for balancing local search and global search.

4. Simulation and Results
In the experiment, we evaluate the number of targets of EAPSO with EA and SA for the problem of target coverage in HDWSNs. The performances of the proposed EAPSO scheme are investigated by simulation. The platform used for simulations is a Pentium IV machine with 2 GB RAM and Matlab is used as programming language.

By simulation experiments, we evaluate their performance with the objective function in section II. Then we generate sensor nodes and targets, and the position of each sensor node and each target is randomly specified within the square area, which takes 500 × 500. The number of targets is 200. Without considering the energy consumption by different sensing ranges, the sensing ranges from 70 to 80 is checked. The number of iterations in EAPSO is fixed at 200.

To illustrate the improvements provided by the EAPSO, the performance is compared with the EA and the SA. Its parameters of the EAPSO, EA and SA are given as following. In EAPSO, we fix the number of populations to 60 particles. The parameter values in the EAPSO are based on a parametric study. The maximum velocity is 3.8. The cognitive and social values take $z_1 = z_2 = 0.5$, $w_{min}$ is 0.2. $w_{max}$ is 0.9. In EA, the population have 60 individuals. Crossover rate is 0.75. Initial mutation rate is 0.08. Gap is 0.9. The temperature in the beginning of SA and the value of annealing temperature are 300 and 0.85, respectively.

![Figure 1. Sensing radius is 70m](image1.png) ![Figure 2. Sensing radius is 80m](image2.png)

Figure 1 shows that the target coverage rate obtained by EAPSO, EA and SA on the target coverage problem with different sensing radius when the amount of nodes is 200. For each method, the coverage rate in every generation is recorded in 200 simulation runs. After iterations, the target coverage rate in figure 1 is close to 0.85 and the target coverage rate in figure 2 is close to 0.96. Therefore, it is clear that the proposed EAPSO yield better results than the adaptive theory and elite theory in terms of the target coverage rate.

As it may be observed in figure 1, at the initial iterations, the number of the target coverage rate of all the heuristics has increased. EAPSO show the overall best behavior, while the EA and SA stagnate. Moreover, for the last 100 iterations, the performance of EAPSO becomes better than EA and SA. In particular, the fast convergence rate is shown clearly that EAPSO is prevented from premature convergence.

Figure 3 shows the number of successfully monitored targets obtained by EAPSO, EA and SA for 200 iterations. It can be seen that the proposed EAPSO found its optimal value of 182 after 200 iterations. In comparison with the EAPSO, EA and SA provide suboptimal results, and the number of successfully monitored targets of EA and SA are 163 and 144, respectively. The results in figure 4 are similar as figure 3. Therefore, the performance of EAPSO is better than EA and SA.

5. Conclusion
Hence, an elite adaptive particle swarm optimization (EAPSO) for target coverage in HDWSNs is proposed. The EAPSO can improve system efficiency while maintaining total system sensing range in
the area. A system model is built to maximize the target coverage rate. Simulations display the performance of the EAPSO compared to EA and SA. The results demonstrate that the EAPSO method provides a larger amount of successfully monitored target over the current EA and SA methods.

![Figure 3. Sensing radius is 70m](image)

![Figure 4. Sensing radius is 80m](image)

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