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Novel RPSO Based Strategy for Optimizing the Placement and Charging of a Large-Scale Camera Network in Proximity Service

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ABSTRACT Sensor placement and charging in proximity service are becoming critical issues. In this paper, novel methods are proposed to address the coverage optimization problem and charging problem of camera networks with mobile nodes. Because the sensing angle of a camera is limited, the placement of a camera network is more complicated compared with an omnidirectional sensor network. Aiming at finding the best positions and working angles of all camera nodes in the coverage optimization problem, we propose a novel resampling particle swarm optimization (RPSO)-based process. First, the RPSO is introduced, which has better precision and efficiency than the PSO and the genetic algorithm. Second, because of the huge number of variables in the problem, we propose a hierarchical strategy, which divides the whole optimization process into several sub-processes in consideration with overlay redundancy and coverage area of all camera nodes, reducing the variables at each step. In this way, the precision of optimization results could be improved significantly. After deploying the camera network, we consider charging it to extend its lifetime. Fuzzy c-means, a fuzzy clustering algorithm, is used to classify the sensor nodes according to their positions. Then, a charging station is set in each cluster, the position of which is determined based on the RPSO to minimize the distance from it to all of the sensor nodes in the cluster. So, the charging efficiency is improved than before. The experimental results show that the proposed methods achieve the goal of maximizing the coverage rate and improving the charging efficiency of the camera network in comparison with the traditional methods.

INDEX TERMS Smart world, sensor placement and charging, hierarchical strategy, resampling particle swarm optimization, fuzzy clustering.

I. INTRODUCTION

In proximity service(ProSe), sensor networks are deployed in many different applications to percept information and transmit data. They would become shared infrastructure serving multiple users. For the purpose of public surveillance and security, camera nodes need to be placed in the target area [1]. In many cases, due to the limitation and the characteristic of the area, the sensor nodes should be placed by aircraft, resulting in the random distribution of sensors, which could lead to the overlapped nodes as well as large uncovered areas. So the monitoring quality would be affected directly. In order to solve this problem, Xu *et al.* [2] assume that each camera is mounted on a mobile platform. After distributed randomly, each nodes can move to a new position constrained by a predefined maximum distance and adjust its orientation for the sake of maximizing the coverage rate of the surveillance region. Furthermore, because camera nodes acquire energy only from batteries, they should be charged before the depletion of energy so that the camera network can work continuously.

In the field of coverage optimization problem, camera sensor, as a directional sensor, is limited by both working directions and the field of view(FoV). Unlike the omnidirectional sensor networks, the coverage rate of a camera network depends on not only the positions and sensing distances of all the nodes, but also the working direction and the FoV.

Many researchers have studied the coverage optimization of sensor network. The virtual force between adjacent sensors is utilized to improve the coverage rate [3], [4]. The particle swarm optimization, as a well known method with its simplicity, fast convergence and high quality results [5], is also used to obtain the best coverage [2], [6]–[8]. In [6], the cameras cannot move and only the working angles of them can be adjusted, which limits the effect of optimization. Aziz *et al.* [8] introduced the PSO and Voronoi diagram in the sensor deployment, the optimal positions of the sensors are obtained by PSO to get the best coverage, while the Voronoi diagram is responsible for evaluating the fitness of solution. Though PSO has many strengths, it is still easy to get trapped in a local optimum prematurely and after many iterations, some particles might still be far away from the potential optimal position, which called 'moving lag'. Aiming to address this problem, in our previous work, we introduce the re-sampling process to PSO inspired by the particle filter and propose resampling particle swarm optimization(RPSO) [9]. Experiments show that both the computational efficiency and optimal solution are improved after adopting RPSO. However, there are still some limitations in optimization due to the attribute of PSO and RPSO, as the variable number of the optimization increases, the global search ability of them become weaker. In [2] and [10], the number of camera nodes optimized by PSO is only a few or less than twenty. So the optimization of large-scale sensor deployment is limited. Zhang *et al.* [11] and Sung and Yang [12] exploit the Voronoi diagram to transform the network area coverage problem into cell coverage problems, which reduces the variable number and the calculation complexity in local area, but it is based on a relatively uniform distribution of the sensors at the initial moment, which is difficult to realize because of the random distribution by aircraft.

In the field of sensor charging problem, as the wireless power transfer technique make a breakthrough [13], it is possible to solve the energy-constrained problem through recharging energy to sensors in order to prolong the network lifetime. Because of wireless charging technology, sensor nodes can be scheduled to recharge by the mobile charger. The recharge schedule and routing problem is studied in [14], Xie *et al.* prove that the shortest Hamiltonian cycle is the optimal charging path. In [15] and [16], the sensor nodes can be recharged only if the locations of which is in the charging range of the mobile charger. So this method has high restrictions on mobile chargers. A method based on traveling salesman problem is used to minimize the traveling distance to save energy in [17]. Wang *et al.* [18] proposes a dynamic optimal scheduling scheme for the purpose of maximizing the vacation time of a single mobile changer. Furthermore, the number of mobile chargers is also discussed in different cases [19], [20]. Though previous works are able to recharge sensors to prolong the network lifetime, there is still a problem. Due to the characteristic of wireless charging, the closer the distance, the higher the charging efficiency. Therefore, the mobile charger should move to every sensor nodes in turn, which wastes time and has a low efficiency, especially when

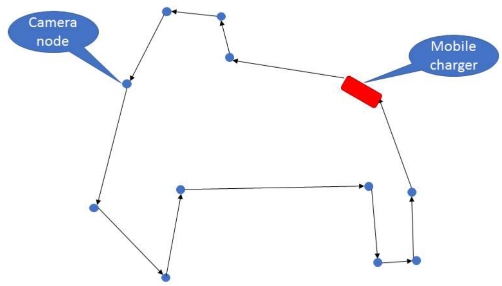

FIGURE 1. Traditional charging.

the number of sensors waiting to be charged is large, as shown in Fig.1.

In this paper, we assume that the camera nodes mounted on mobile platforms are scattered randomly by aircraft in the target region, and then they need to move, updating their locations and working orientations to get the best coverage. Due to the energy limitation, they can only move within the predefined maximum distance. When optimizing the coverage of the camera nodes in the target area, we not only adopt resampling particle swarm optimization(RPSO) instead of PSO, but also propose a hierarchical strategy, dividing the whole optimization process into several sub-processes in consideration with overlay redundancy and coverage area of camera nodes, reducing the variables at each step in order to improve the computational efficiency and the precision of optimal solution. After finishing deploying the camera nodes, the fuzzy c-means algorithm(FCM) is used to cluster the nodes according to their positions. Then, a charging station is set in each cluster, the position of which is determined based on the (RPSO) by minimizing the distance from it to all of the sensor nodes in the cluster. When the network need to be recharged, the camera nodes in each cluster move to their corresponding charging station within the maximum moving distance while a mobile charger would be placed by airplane and come to all charging stations in turn. In this way, all the nodes are charged in the station and then move back to their previous positions, which reduces the moving distance of the mobile charger and improves the charging efficiency greatly, especially when a charger could recharge several sensor nodes at the same time in the future.

The contributions of this paper can be summarized as follows: 1)the RPSO is used to solve the coverage optimization problem, enhancing the efficiency and prompting the ability to avoid getting trapped in local optimum prematurely; 2)because both PSO and RPSO have difficulty in the optimization problem with large number of variables, we propose a hierarchical strategy to improve the computational efficiency and the optimal solution. The whole optimization process is divided into several sub-processes, the nodes with larger overlap degree and smaller coverage area are optimized earlier while the nodes with smaller overlap degree and larger coverage area are considered later, reducing the variable number at each step. 3)we propose a new scheme for network charging, classifying all the camera nodes into several clusters according to their locations based on FCM and setting a charging station in each cluster based on RPSO. The mobile charger do not need to go to every nodes, but to every station and charge the nodes in the corresponding cluster moving to there. As a result, the moving distance of the mobile charger is much shorter and the charging efficiency is higher.

The rest of the paper is organized as follows. In Sect. II, the model of camera nodes deployment and charging is described. In Sect. III, we introduce the resampling particle swarm optimization(RPSO) and the fuzzy c-means algorithm(FCM), then a hierarchical strategy in the optimization process is proposed. The experimental results are presented and analyzed in Sect. IV. In Sect. V, we conclude the paper, pointing out the directions for the future works.

II. THE MODEL OF THE PROBLEMS

In this section, we introduce the model of camera network coverage optimization and the model of network charging.

A. THE MODEL OF CAMERA OPERATIONS

The problem of optimal camera network deployment to cover the monitoring region is presented in this work. Unlike the omnidirectional sensors, the field of view(FOV) of a camera should be considered [4], [21]. As shown in Fig.2, the maximum effective distance of a camera is defined as R and the angle of view is 2β. The working direction α of the camera is defined as the angle between the angle bisector of its FOV and the x-axis. Because the angle of view 2β is determined by the camera type, in order to judge if a point in the target area is covered by the jth camera, we need three parameters: the location (x_j, y_j) and the working orientation α of the camera. Firstly, we judge if the ith point is in the angle of view of the camera, then the distance between it and the camera node is considered (1)

$$P_j = \begin{cases} 1 & |\gamma - \alpha| < \beta \quad and \\ & ((x_i - x_j)^2 + (y_i - y_j)^2)^{\frac{1}{2}} \leq R \\ 0 & other \end{cases} \tag{1}$$

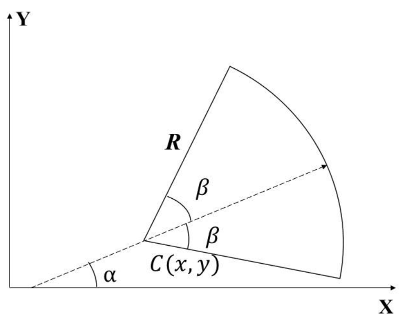

FIGURE 2. The FOV of a camera.

where γ represents the angle between the vector which is from the camera node to the point and the angle bisector of the FOV. The (x_i, y_i) is the coordinate of the ith spot. The equation indicates that if the conditions of angle and distance are both satisfied, the point is covered by the jth camera and its monitoring probability P_j is set to 1, otherwise it is set to 0.

B. THE COVERAGE OPTIMIZATION MODEL

For the purpose of calculating the coverage of the target region, we divide the area into $t * s$ grids, taking the center (x_i, y_i) as the representative of the ith grid. If the ith grid is considered to be covered, if at least one camera covers its center; that is, its monitoring probability P_i is 1.

$$P_i = 1 - \prod_{j=1}^{n}(1 - P_j) \quad j = 1, 2, \cdots, n \tag{2}$$

Then we calculate the coverage of target area (3).

$$f_1 = \frac{\sum_{i=1}^{t*s} P_i}{t * s} \tag{3}$$

In addition, because all camera nodes have a maximum moving distance, the constraint must be satisfied, shown as follows (4):

$$\sqrt{((x_j - x_{j0})^2 + (y_j - y_{j0})^2)} \leq distance(max) \qquad j = 1, 2, \cdots, n \tag{4}$$

where the (x_{j0}, y_{j0}) is the initial location of the jth camera node.

After that, we adopt RPSO combined with a hierarchical strategy to get the optimal deployment of the camera nodes, obtaining the best coverage.

C. THE NETWORK CHARGING MODEL

As shown in Fig.3, we propose a new scheme for network charging. Firstly, all camera nodes are divided into several clusters according to their locations based on FCM. Then, a charging station is set in each cluster. The mobile charger do not need to go to every nodes, but to the station and charge the nodes in the corresponding cluster moving to there, which can reduce the moving distance of the mobile charger and improve the charging efficiency. After charging, all the nodes go back to their previous positions and go on working.

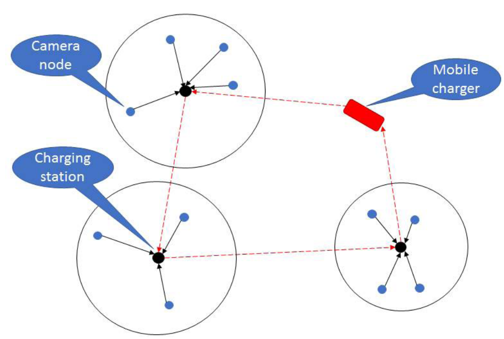

FIGURE 3. A novel charging strategy.

The number of charging stations should be determined according to the actual demands. When the number of charging stations decreases, the moving distance and the moving time of the mobile charger might decrease, and the charging efficiency might increase, especially when a charger could recharge several sensors at the same time. In this way, the charging time of the network might be reduced greatly but the moving distance of sensors might increase. In addition, the cluster number m should beyond a threshold because of the maximum moving distance of all the sensor nodes otherwise many nodes can not be able to access the stations. The threshold is as follows (5):

$$m > \frac{S}{\pi * (distance(max))^2} + b \tag{5}$$

where S is the total area of the target region, b is a natural number which is adjusted as small as possible under the conditions of ensuring all the sensor nodes can reach the charging station in their clusters.

When selecting the charging station in a cluster, the location of which should also be optimized. Because every camera nodes in the cluster should arrive at it to be recharged, it is of great significance to minimize the distance from it to all of the sensor nodes in this cluster. Therefore, we assume n camera nodes is divided into m clusters, the objective function is as follows (6):

$$f = \sum_{l=1}^{m} \sum_{j=1}^{k_l} \sqrt{(x_l - x_{jl})^2 + (y_l - y_{jl})^2} \tag{6}$$

where k_l, (x_l, y_l) represents the number of nodes and the location of charging station in the $No.l$ cluster respectively, and the (x_{jl}, y_{jl}) indicates the coordinates of the jth camera node in the lth cluster. Then, because all the nodes have a maximum moving distance, the constraint should be satisfied (7).

$$\begin{aligned} \sqrt{((x_l - x_{jl})^2 + (y_l - y_{jl})^2)} &\leq distance(max) \\ j &= 1, 2, \cdots, k_l \\ l &= 1, 2, \cdots, m \end{aligned} \tag{7}$$

Finally, we use RPSO to get the optimal locations of the charging stations, making the moving distance of all the camera nodes the shortest.

III. ALGORITHM

A. RESAMPLING PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) is widely used because of its high-performance and flexibility. However, there are two potential problems of the classical PSO:

- Because of the random positions and velocities of the initial particles, it is extremely possible that some particle are still far away from the potential best position even after many iterations, which is called moving lag. It decreases the speed of the whole groups gathering to a better position, and the particles with this bad condition result in a waste of calculation resources.
- For some large scale, high dimensional, and multi-peak optimization problems, it is difficult for PSO to get the real global optimal solution, because of the lack of ability to jump out an attraction basin.

To overcome the shortcomings mentioned above and improve the performance of PSO, the resampling process, inspired by the Particle Filter (PF) [24], [25], is introduced to PSO. The new optimization algorithm is called Resampling Particle Swarm Optimization (RPSO).

The main steps for resampling are as follows:

1) Define the standard of resampling. During the specific iteration procedure, if the standard of resampling is met, the resampling process would be executed.

2) Give each particle a weight value as Equation (8) and Equation (9).

$$q_i = \frac{1}{\sqrt{2\sigma\pi}} exp(-\frac{(F(x_i) - p_g)^2}{2\sigma}) \tag{8}$$

$$Q_i = \frac{q_i}{\sum_{i=1}^{N} q_i} \tag{9}$$

where q_i is the weight value given to particle i, $F(x)$ is the fitness function, p_g stands for the current global optimal value, σ is the sample variance of $F(x_i) - p_g$. Q_i is the unitary weight value given to particle i.

3) For each particle, if $Q_i < q_t$, then

$$Pr(x_i(t) = \bar{x}_i(t)) = Pr \tag{10}$$

where $\bar{x}_i(t)$ is the new position introduced randomly. The way to update velocities is shown in (11).

$$v_i(t) = \frac{T + t}{2T} \bar{v}_i(t) + \frac{T - t}{2T} v_i(t) \tag{11}$$

where T is the maximum step of iteration, and $\bar{v}_i(t)$ stands for a new velocity we introduce randomly. This equation expresses that the velocity would be updated under the influence of the original velocity and the new velocity we introduced, and the later the iteration is, the bigger influence the new velocity makes.

The RPSO, introducing the resampling technique to PSO, makes up for the potential problem of PSO and enhances its performance. The pseudo code of RPSO is presented in Algorithm 1.

B. THE HIERARCHICAL STRATEGY IN COVERAGE OPTIMIZATION PROCESS

Though RPSO is more precise and more efficient than PSO in the global optimization problem, it still easy to get trapped into local optimum when the dimension is too high. In the large-scale camera network deployment problem, it needs three variables to place a ith camera (x_i, y_i, and the working angle α_i). As the number of cameras increasing, the dimension of the optimization problem expands fast. In order to maximize the effectiveness of the RPSO and get better optimal solution, we propose a hierarchical strategy, dividing the whole optimization process into several sub-processes in consideration with overlay redundancy and coverage area

Algorithm 1 RPSO Algorithm

given the size of the swarm$N$, the maximum step of iteration T
set $i = (1, ..., N)$, $t = 0$
initialize the particles $x_i(0)$, $p_i(0)$, $v_i(0)$
while convergence is not arise, do
  for each time step t, do
    if the standard of resampling is met, then
      for each particle i, do
        $q_i = \frac{1}{\sqrt{2\sigma\pi}} exp(-\frac{(F(x_i)-p_g)^2}{2\sigma})$
        $Q_i = \frac{q_i}{\sum_{j=1}^{N} q_i}$
        if $Q_j < q_t$ do
          $x_i(t) = \bar{x}_i(t)$
          $v_i(t) = \frac{T+i}{4T}\bar{v}_i(t) + \frac{2T-i}{4T}v_i(t)$
        end if
      end for
    end if
    for each particle i, do
      $v_i(t+1) = \chi\{v_i(t)+c_1r_1[p_i-x_i(t)]+c_2r_2[p_g-x_i(t)]$
      $x_i(t+1) = x_i(t) + v_i(t+1)$
      update $p_i(t+1)$, $p_g(t+1)$
        $p_i(t+1) = best\{p_i(t), f(\mathbf{X}_i(t+1))\}$
        $p_g(t+1) = best\{p_i(t+1)\}$
    end for
  end for
end while
return p_g^*

of all camera nodes. The nodes with larger overlap degree and smaller coverage area are selected to be optimized earlier while the nodes with smaller overlap degree and larger coverage area are considered later. Therefore, at each step, the number of variables is restricted to less than 20, improving the precision of the final results.

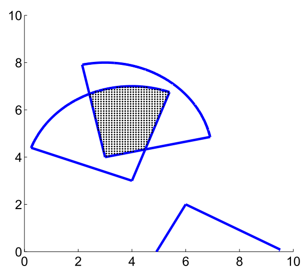

FIGURE 4. Nodes with overlap and small coverage.

As shown in Fig4, the overlap degree of a camera node is the ratio of the overlap area to its full surveillance area. In addition, the coverage area of the node also should be considered when its location is close to the area boundary. We define the nodes with large overlap degree or with small coverage area as 'bad nodes' because they contribute little to the coverage. In the strategy, at each step, we adjust the threshold about the overlap degree and coverage area, selecting the relatively 'bad nodes' to be optimized while maintaining the positions of other nodes. At the beginning, the threshold 1 (overlap degree) is high and the threshold 2 (coverage area) is low, the 'bad nodes' which beyond the threshold 1 or under the threshold 2 are optimized firstly. As the steps increasing, the threshold 1 is decreased and the threshold 2 is increased gradually to select and eliminate relatively bad nodes continuously until the optimal solution is obtained. The pseudo code of the hierarchical strategy is presented in Algorithm 2.

Algorithm 2 The Hierarchical Strategy in Coverage Optimization

function select
for $step = 1 \rightarrow t$ **do**
  for $j = 1 \rightarrow n$ **do**
    compute the overlay degree and coverage area of the *jth* camera node
    set the threshold to select 'bad nodes' to be optimized
    if overlay degree(j)>1-Steplength1$*t$ or
      coverage area(j)< initial value+Steplength2$*t$
    do
      select the *jth* node in the optimization process
    end if
  end for
  use RPSO to optimize the selected nodes to get the best coverage
end for
end function

C. FUZZY CLUSTERING ALGORITHM

In the classical non-fuzzy clustering (hard clustering), objects in basic set are divided into distinct subsets, where each object can only belong to one exactly subset. However, in some situations, the clusters are much more complex, the belongingness of the objects to which is vague. Therefore, the fuzzy clustering has been proposed [22].

One of the most widely used fuzzy clustering algorithm is the Fuzzy C-mean clustering (FCM) algorithm [23]. Its idea is to maximize the similarity between objects divided into the same cluster, minimizing the similarity between different clusters. In FCM algorithm, a finite collection of n elements $X = \{x_1, \cdots, x_n\}$ are partitioned into a collection of c fuzzy clusters $C = \{C_1, \cdots, C_c\}$ with respect to some given criterion. And return an $n \times c$ matrix $M = [\omega_{ij}](1 \leq i \leq n, 1 \leq j \leq c)$, where each element, ω_{ij}, tells the degree to which element, x_i, belongs to cluster C_j.

the ω_{ij} must meet some constraint conditions (12)

$$0 < \omega_{ij} < 1$$
$$\sum_{j=1}^{c} \omega_{ij} = 1 \tag{12}$$

The center of cluster $C_j, 1 \leq j \leq c$ is represented by c_j, then the degree of belonging-ness of object x_i to

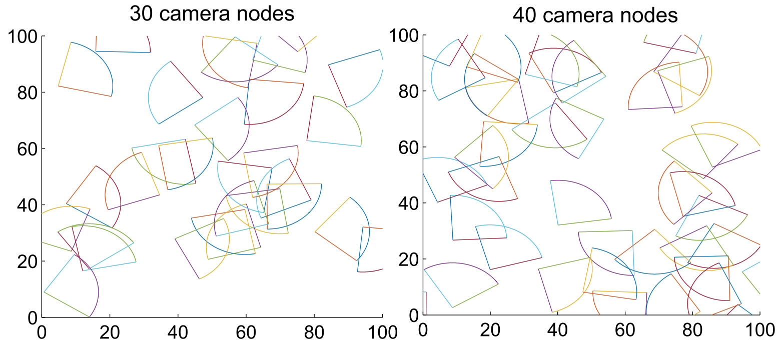

FIGURE 5. Initial placement of camera nodes.

cluster C_j, ω_{ij}, is shown in Equation (13)

$$\omega_{ij} = \frac{\frac{1}{\|x_i - c_j\|^2}}{\sum_{k=1}^{c} \frac{1}{\|x_i - c_k\|^2}} \tag{13}$$

The equation shows that the closer the distance between the object x_i and the cluster center c_j, the greater possibility that the object x_i belongs to the cluster C_j. The pseudo code of FCM algorithm is presented in Algorithm 3.

Algorithm 3 FCM Algorithm

function FUZZYCLUSTERING(k, n)
  for $j = 1 \rightarrow c$ **do**
    $C_j = x_{random(1,n)}$
  end for
  repeat
    for $i = 1 \rightarrow n$ **do**
      for $j = 1 \rightarrow c$ **do**
        $\omega_{ij} = \frac{\frac{1}{\|x_i - c_j\|^2}}{\sum_{k=1}^{c} \frac{1}{\|x_i - c_k\|^2}}$
      end for
    end for
    for $j = 1 \rightarrow c$ **do**
      $c_j \leftarrow \frac{\sum_{i=1}^{n} \omega_{ij}^2 x_i}{\sum_{i=1}^{n} \omega_{ij}^2}$
    end for
  until c_j does not change for $j = 1 \rightarrow c$
  return ω
end function

IV. SIMULATION EXPERIMENT AND RESULTS ANALYSIS

In order to confirm the effectiveness of the proposed RPSO combined with the hierarchical strategy in the coverage problem and the rationality of the proposed novel charging strategy, experiments are designed and implemented on MATLAB 2017a software platform. The size of the monitoring region is set to $100m * 100m$, where a certain number of camera nodes are scattered randomly by the aircraft. The working radius r_s of all the camera nodes is $16m$ and the angle of view is $\pi/4$. Then, the experiments is carried out. They are conducted on a Core i5-3450 3.1 GHz PC with 8GB memory, running Windows 7.

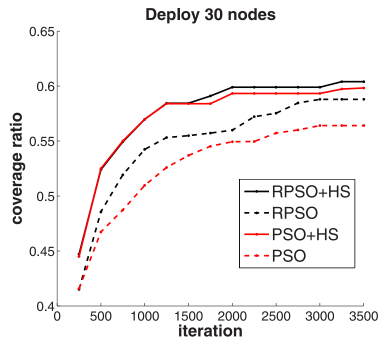

FIGURE 6. Average simulation results of deploying 30 camera nodes.

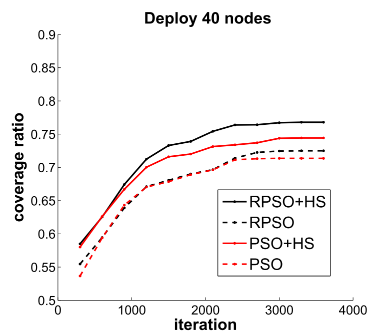

FIGURE 7. Average simulation results of deploying 40 camera nodes.

A. THE COVERAGE OPTIMIZATION EXPERIMENT

Two cases are studied in this experiment. In case 1, 30 camera nodes are deployed in the target region and in case 2, 40 camera nodes are placed in it. In addition, all the cameras are of type $(R, \alpha) = (16, \pi/4)$. In each case, the nodes are randomly scattered in the region and then they move and update their positions to get the best coverage constrained by a predefined maximum distance, which is set to 30. We compare the optimal results obtained by PSO, RPSO, PSO combined with the hierarchical strategy (PSO+HS) and RPSO combined

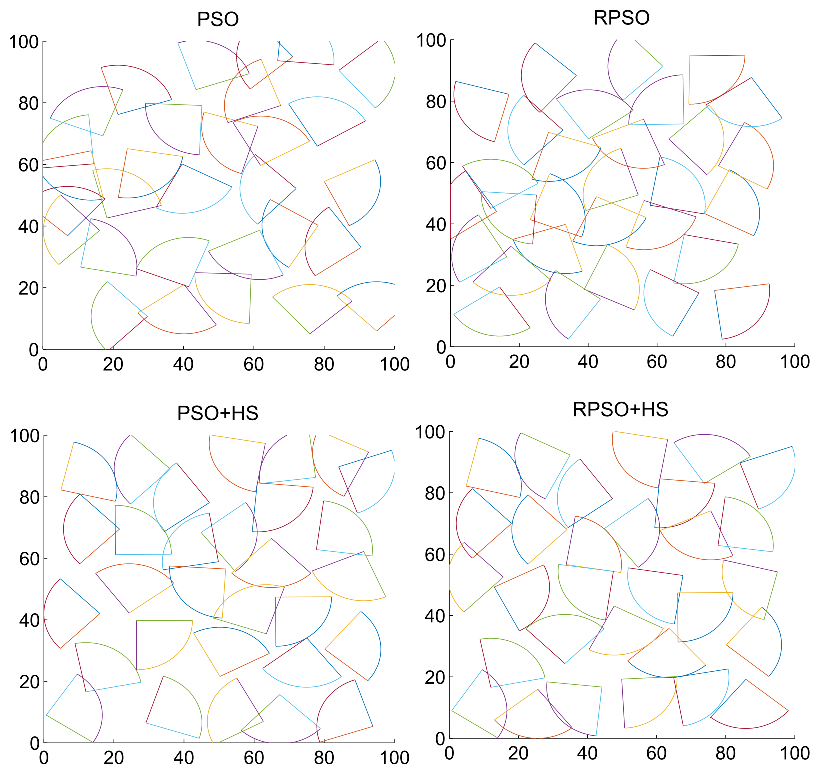

FIGURE 8. The best locations of 30 camera nodes after optimization.

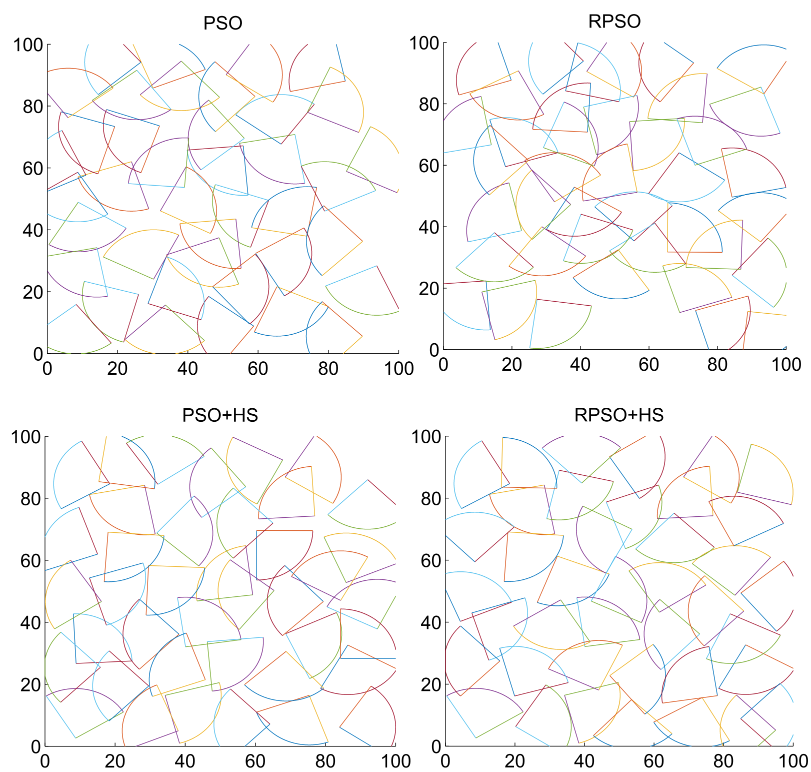

FIGURE 9. The best locations of 40 camera nodes after optimization.

with the hierarchical strategy (RPSO+HS). To ensure the reliability of the results, in each algorithm, we run ten times, calculating the average value of fitness about the coverage ratio. The initial deployments of case 1 and case 2 are shown in Fig.5 and the final deployments after optimization is shown in Fig.8 and Fig.9 respectively. Table 1 presents

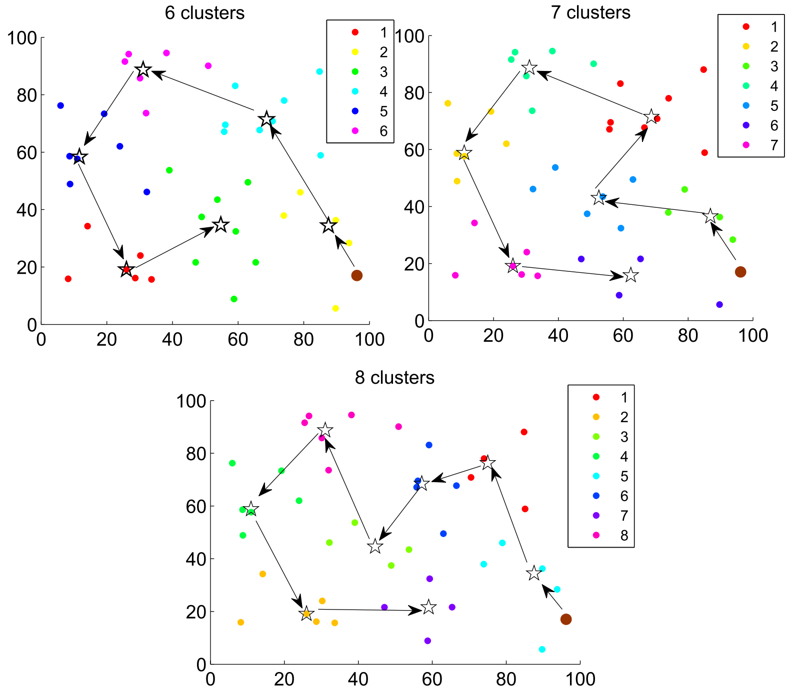

FIGURE 10. The charging stations of 6,7,8 clusters respectively after optimization.

the optimal results gained by every method in each case.

TABLE 1. Comparison of PSO,RPSO,PSO+HS and RPSO+HS in coverage optimization cases.

30 camera nodes	PSO	RPSO	PSO+HS	RPSO+HS
mean	0.5641	0.5879	0.6003	0.6030
min	0.5451	0.5683	0.5983	0.5997
max	0.5965	0.5998	0.6035	0.6041
40 camera nodes	PSO	RPSO	PSO+HS	RPSO+HS
mean	0.7036	0.7251	0.7438	0.7657
min	0.6576	0.6749	0.7272	0.7582
max	0.7491	0.7525	0.7592	0.7703

From Fig.6 and Fig.7, we can find that the coverage ratio start to increase as the number of iterations expand and converge to the maximum value finally. In case 1, the coverage ratio is approximately increased from $0.4-0.45$ to $0.55-0.6$ and in case 2, the coverage ratio is improved from $0.5-0.6$ to $0.7-0.77$ because the number of cameras in case 2 is more than that in case 1. In each case, the optimal results obtained by the four methods satisfy this relation: $RPSO+HS > PSO+HS > RPSO > PSO$.

Table 1 shows us the optimal results of PSO,RPSO, PSO+HS and RPSO+HS. Compared with PSO, the mean, maximum and minimum value of RPSO are all higher in each case, RPSO promotes about $0.3\%-0.4\%$ in the max coverage ratio and $2\%-3\%$ in the mean coverage ratio after running ten times. During the experiments, RPSO can not only get better max coverage value than PSO, but also perform more stable than PSO, for the interval size of results gained by RPSO (3.15% in case 1 and 7.76% in case 2) is smaller than which gained by PSO (5.04% in case 1 and 9.15% in case 2).

Though RPSO performs better than PSO, it is still unable to get more precise solution compared to RPSO+HS, especially when the number of variables to be optimized is large. From table 1, we can find that after combining with the hierarchical strategy, the optimal solutions of PSO and RPSO improve significantly. For PSO+HS, the max coverage ratio is increased by 0.7% in case 1 and 1.01% in case 2 compared to PSO. On the other hand, the interval size of results is reduced from 5.04% to 0.52% in case 1 and from 9.15% to 1.54% in case 2. For RPSO+HS, the max coverage ratio is increased by 0.43% in case 1 and 1.78% in case 2 compared to RPSO. And the interval size of results is reduced from 3.15% to 0.44% in case 1 and from 7.76% to 1.21% in case 2.

It is clear that the proposed RPSO+HS performs best among the four methods, the optimum coverage ratio of which can reach 0.6041 in case 1 and 0.7703 in case 2, which is the highest of all. In comparison with the traditional PSO, the max coverage ratio is increased by 0.76% in case 1 and 2.12% in case 2 while the interval size of results is reduced from 5.04% to 0.44% in case 1 and from 9.15% to 1.21% in case 2. Therefore, the RPSO combined with the hierarchical strategy (RPSO+HS) can solve the optimization problem better, getting more accurate solutions and performing much more stable. The strengthen of RPSO+HS become more obvious as the camera number expands, for it is good at handling coverage optimization problem with more variables.

We can also evaluate the methods through Fig.8 and Fig.9. Obviously, both in case 1 and case 2, the placement obtained by RPSO+HS cover the largest area, the bad nodes with high overlap degree and low coverage area is the least among other pictures.

B. THE CHARGING EXPERIMENT

After getting the best placement of camera nodes in the target region, we consider recharging them to prolong network lifetime. In this experiment, all the nodes are divided into 6, 7, 8 clusters respectively. As shown in Fig.10, every color represents a cluster, the brown spot represents the mobile charger while the arrow indicates the moving path of it. The charging station of each cluster (labeled as star) is selected based on RPSO, minimizing the moving distance from all the nodes in the cluster to it. Therefore, the mobile charger do not need to go to every nodes, but to every station and charge the nodes in the corresponding cluster moving to there. After charging, all the nodes go back to their previous positions and continue to work. In this way, the time wasted by the charger's moving process is reduced and the charging efficiency is improved, especially when a charger could recharge several sensors at the same time.

The distance optimization process is shown in Fig.11 and the moving distance of camera nodes and mobile charger in each scenario is presented by Table 2.

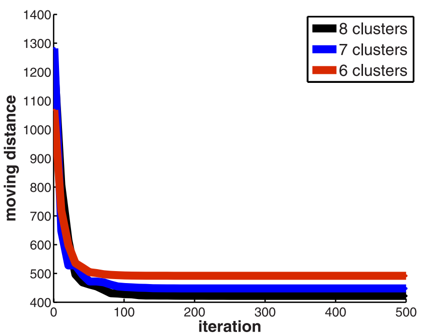

FIGURE 11. The moving distance of camera nodes after optimization.

TABLE 2. Results of the charging strategy.

6 clusters/moving distance	camera nodes	mobile charger
mean	491.81	193.39
min	491.78	193.35
max	491.83	193.42
7 clusters/moving distance	camera nodes	mobile charger
mean	447.90	224.18
min	447.84	224.11
max	448.95	224.23
8 clusters/moving distance	camera nodes	mobile charger
mean	421.98	251.20
min	417.29	242.12
max	426.34	257.86

In Fig.11 and Table 2, the average distance from a camera node to the station is about $10.4 - 12.3$. We can find that as the number of cluster and its corresponding charging station increases, the moving distance of camera nodes reduces but the moving distance of charger increases. Therefore, the cluster number can be adjusted based on the demand in the actual situation.

V. CONCLUSION AND FUTURE WORK

In this paper, novel methods are proposed to address the coverage optimization problem and charging problem of camera networks with mobile nodes. We find the best positions and working angles of all camera nodes in the coverage optimization problem and improve charging efficiency though a novel strategy. The conclusions of this paper could be summarized as follows.

1) RPSO is adopted in the coverage optimization problem. In this algorithm, particles with low value would be eliminated and replaced, improving the efficiency of the algorithm and making it easier to get a better solution. The experiments show that compared to PSO, the optimal results of RPSO is more precise.

2) Because both PSO and RPSO have difficulty in the optimization problem with large number of variables, we combine RPSO with a hierarchical strategy (RPSO+HS) to improve the computational efficiency and get better optimal solution. The experiments show that it gets higher coverage ratio and performs much more stable than PSO, RPSO and PSO+HS. The strengthen of RPSO+HS become more obvious as the camera number expands, for it is good at handling the coverage optimization problem with more variables.

3) A new charging strategy is proposed, dividing all camera nodes into several clusters and setting a charging station in each one. The mobile charger go to every station and charge camera nodes moving to there. In this way, the charging efficiency is improved, especially when a charger could recharge several sensors at the same time.

For the future work, we would like to investigate the following issues. Firstly, we would improve the RPSO to make it more efficient and easier to get more precise optimal solutions. Secondly, because the optimal camera placement obtained in the coverage optimization experiment could affect the optimal location of charging stations in the charging experiment, the whole process can be seemed as a two-stage optimization problem and we would study it. Then, the connectivity issues would also be considered [26], [27]. Finally, the charging process would be further discussed, the optimization problems of which would be studied based on the novel charging strategy.

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