Sensor Deployment Method Based on Faiw-DPSO in DASNs

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\textbf{Abstract} Distributed Active Sensing Networks (DASNs) is a new sensing paradigm, where active and passive sensors are distributed in a field, and collaboratively detect the objects. The detectability is the most important property of DASNs. “Exposure” is defined to quantify the dimension limitations in detectability. Thus, it is important to deploy the sensors with the minimum exposure to improve the detectability. To minimize exposure is NP-hard, thus it is necessary to solve it by heuristic algorithms. In this paper, we present a Discrete Particle Swarm Optimization (DPSO)-based solution to achieve the minimum exposure. Furthermore, a feedback-based adjustment on the inertia weight of DPSO is designed to improve the convergence speed and global searching ability of algorithm. By a large number of simulations, this improved DPSO (Faiw-DPSO) is proved to outperform greedy algorithm by up to 74% and perform better than other related algorithms. This algorithm is robust, efficient and self-adaptive in regular and irregular monitoring field.

\textbf{Index Terms} Distributed active sensing networks (DASNs), discrete particle swarm optimization (DPSO), exposure, feedback-based adjustment, inertia weight.

I. INTRODUCTION

Recent years have witnessed the increasing interests in target detection and localization in wireless sensor networks (WSNs) [1]. Much research has been conducted on passive sensor networks, where it is assumed the targets themselves can emit or reflect signal (light, magnetic, acoustic) for detection. Active sensing networks, on the other hand, employ active sensors (or actuators), which emit waveforms (acoustic or electro-magnetic), and passive sensors as receivers. Presence and characteristics of targets are detected by the changes they induce in wave propagation in the medium. Most existing active sensing systems are independent systems with co-located transmitters and receivers. Applications of active sensing include, i) deformation detection using piezoceramic-based transducers that can transform electrical voltage to elastic stress waves and vice versa [2], [3]; ii) detection of intruders using laser emitters and receptors in security systems [4], [5]; iii) underwater sound navigation and ranging (Sonar) systems [6]; and (iv) modern power system smart grids (SGs) [7]. These systems differ in the sensing modalities used and the propagation medium involved. However, all share the common advantage of not being restricted by environmental illumination conditions, and thus they are critical for detecting targets that are “stealthy” and/or non-cooperative. Distributed active sensing networks (DASNs) is thus defined as a collection of active and passive sensors distributed in a field to perform sensing tasks cooperatively [8]. DASNs are essentially different from passive sensor networks in that sensing is performed in pairs (between an actuator and a sensor), as opposed to at a single node.

The problem of the optimal deployment of sensors/actuators in WSNs especially in active sensor networks is of considerable interest in network design where improved robustness and efficiency of network structure. The optimization procedures for actuators/sensors deployment are...
usually based on different performance metrics adopted as criteria for optimization like maximizing coverage [9]–[11], enhancing connectivity [12], [13], and minimizing energy consumption [14], [15], etc. However, different criteria have their own limitations. Therefore, it is impossible to establish a unique criterion to obtain the unique solution of the optimization problem. On the other hand, these performance metrics (coverage, connectivity and energy consumption) of sensor deployment are only applicable to passive sensor networks and independent active sensing system. As for DASNs, the detectability, which can illustrate how effective are actuators/sensors in detecting obstacles, and what is the condition for an obstacle to be detectable, is the fundamental property of DASNs [8]. To our best of knowledge, we are the first one to optimize the actuators/sensors deployment considering the detectability of DASNs with the help of “exposure” introduced in our previous work.

In our previous work [16], the concept of “exposure” was introduced. It was designed to quantify the dimension limitations in detectability, i.e., the dimension of obstacles which cannot be detected by actuators and sensors arrangement. More specifically, given the deployment of sensors and actuators, exposure is the radius of the largest objects that cannot be detected [16]. It considers the indicators that affect the detectability of DASNs, including the deployment of visible actuators and sensors, as well as physical media and environmental layout. It is deployment centric and independent of the detailed characteristics of the obstacle. The worst case detectability of DASNs can optimize by minimizing exposure. In this paper, we consider the problem of the optimal deployment of active sensors for target detection with the objective to minimize exposure. However, the problem of minimizing exposure has been proven to be an NP-hard problem [16]. So heuristic solutions need to be devised. In our previous work, we have applied other heuristic algorithms to solve sensor deployment, such as GA [16], Gibbs sampler [17]. We find that GA is relatively complex in calculation, weak in searching ability and poor in convergence speed, while Gibbs sampler for multi-dimensional problems, that is, when there are a large amount of sensors, the optimization effect is not obvious. Because DPSO has the advantages of parallelization, high speed and handy calculation, it can improve the efficiency and optimization effect when it is applied in sensor deployment. More specifically, a 2-D flat binary particle encoding is used to represent sensor locations. A quality index is defined that takes into account of both minimizing the exposure and evenly partitioning the monitoring field. At the same time, a feedback-based adjustment mechanism on inertia weight of DPSO is designed to further improve the convergence speed and global searching ability of algorithm.

The simulations show that the improved DPSO (Faiw-DPSO) algorithm has advantages in sensor deployment of DASNs. It can indeed achieve smaller exposure compared to other heuristic algorithms with fast convergence speed. It outperforms a simple greedy algorithm by up to 74% and is better than other more heuristic algorithms in performance of solution as well as convergence speed.

The rest of the paper is organized as follows. In Section II, closely related work of WSNs is introduced. In Section III, the sensor deployment models and related preliminaries are introduced, and the concept of exposure is described. In Section IV, the Faiw-DPSO algorithm is presented in details and applied in sensor deployment. A large a number of comparative evaluation is provided in Section V before conclusions are drawn in Section VI.

II. RELATED WORK

The sensor deployment problem in passive sensing networks has been studied extensively in the literature. In general, sensors are arranged to achieve some optimization goals, such as area coverage, network connectivity, energy efficiency etc. [18]. Dealing with area coverage problem, the bulk of existing research assumes a disk coverage zone centered at the sensor with the sensing range being the radius [19]. Much sensor deployment research is based on the simple disk coverage modal [20], [21], [25]. However, the simple disk coverage model does not consider the physical medium and environment layouts around monitoring field. Further studies introduce the sensor deployment approaches based on coverage considering environmental factors. In [26], H. Z. Abidin et al. proposed a sensor placement technology based on minimax algorithm, which monitors the location from the nearest sensor node. By comparing the performance of minimax and ideal in coverage, the coverage of minimax technology is proportional to the number of sensor nodes. In [9], Dhillon et al. took into account the terrain and sensing inaccuracy factors, due to which, an object may be undetectable. The authors proposed a greedy searching approach to solve the sensor placement such that the minimum application-specified confidence level is achieved using the least number of sensors. However, this paper implements and tests an unreal terrain model and terrain obstacle model. Besides, their greedy algorithm has the risk of easily falling into local optimum. Besides, J. J. Yang et al. took into account quantifying trade-off relationship between coverage rate and cost in their research [27]. The authors proposed a novel sensor model in a three-dimensional (3D) space for sensor deployment, so that the coverage rate can be evaluated in 3D space. The 3D model and the corresponding 3D coverage rate evaluation method are shown to be effective.

Since sensing coverage and network connectivity are two of the most fundamental properties in WSNs [28], some researchers try to deploy the sensors to achieve both full coverage and strong connectivity. In [29], C. Wei et al. provided an optimal regular deployment patterns taking advantage of data fusion to achieve information coverage and connectivity. The deterministic deployment they used is critical since it can’t ensure that the coverage is truly effective in a real environment. In [30], a self-deployment of sensors in underwater acoustic sensor networks (UWASN) was provided aiming at achieving maximum coverage and guaranteeing connectivity.
But self-deployment cannot provide a solution for static sensors that need to be deployed in specific application scenario such as environment monitoring. In [31], H. P. Xu et al. proposed two heuristic algorithms for achieving both a wide range of coverage and high-performance connectivity. The research is based on their proposed confident information coverage model. One heuristic algorithm aims at constructing a connected cover for confident information coverage in a greedy manner. And the other first places some sensors to cover all of the grid points in a greedy manner without considering network connectivity, then checks whether the deployed sensors can form a connected network. Similarly, J. Zhu et al. also proposed greedy heuristic algorithms for achieving confident information coverage [32]. However, the approaches introduce very high computation complexity since the number of grid vertices has to be set large enough so as to represent the continuous field. So it is also a kind of grid-based method to solve sensors placement especially in irregular sensing field.

As for continuous sensing field especially for the field in irregular shape, it is difficult to determine the position of the sensor completely. Therefore, the grid method is used to grid the continuous field into grid points, and each sensor is placed in the center of grid. This method is especially suitable for the sensing field in irregular shape. W. C. Ke et al. proved that the problem of deploying sensors on grid points to construct a WSN that fully covers critical grids using minimum sensors is NP-complete in [33], and the Steiner tree-based critical grid covering algorithm (STBCGCA) is proposed to solve this problem in [34]. Reference [35] try to place the least number of sensors in the field such that the targets can be detected with high probability. The authors proposed two enhanced algorithms for constructing a minimum size WSN with full coverage of critical grids so that the targets are guaranteed to be detected with desired confidence. The two proposed algorithms consider how to use sensors to cooperatively cover critical grids in an attempt to minimize the number of deployed sensors.

The sensor deployment problem has also been addressed computational geometry field. Specifically, Voronoi diagrams and Delaunay triangulation (DT) have been used to estimate the coverage region of a sensor [36]. As for DT, H. Chizari et al. proposed a new coverage measurement method using DT [37]. This can provide the value for all coverage measurement tools. Moreover, it categorizes sensors as ‘fat’, ‘healthy’ or ‘thin’ to show the dense, optimal and scattered areas. It can also yield the largest empty area of sensors in the field. This tool can achieve accurate coverage information, and provides many tools to compare QoC between different scenarios. Thus, H. W. Chun et al. proposed a centralized and deterministic sensor deployment method, Delaunay Triangulation-Score (DT-Score), aims to maximize the coverage of a given sensing area with obstacles [38]. In [11], the problem of sensor placement is considered as a constrained optimization problem, and a sensor placement scheme based on improved GA and DT is proposed.

The scheme can generate effective chromosomes to ensure coverage and connectivity, so that the least number of sensor nodes are placed in the area with obstacles to ensure the reliable coverage of information and connectivity of nodes. In [38], a two-phase sensor deployment using iterative DT is proposed. It first places sensors evenly along the contour lines of the boundaries and obstacles. Then it places a new sensor applying the DT to identify the largest coverage hole.

For the network structure based on Voronoi diagram, each sensor is responsible for covering its Voronoi unit. If all Voronoi vertices of Voronoi unit are within the coverage of the sensor, there is no coverage hole in the network. Based on this idea, G. Wang et al. designed two bidding protocols to guide the movement of mobile sensors in a sensor network with a mix of mobile and static sensor. In the protocols, static sensors detect coverage holes locally by using Voronoi diagrams [39]. In [40], J. Xiang propose a sensors locations mechanism used hybrid network by detecting sensing holes using Voronoi diagram. On the basis of better layout effect, it can reduce the energy consumption by the static networks. However, only static network is applicable. The research of [41] which proved practical is to detect the coverage area of wireless sensor network in metro tunnel, which is based on spatial density network Voronoi diagram. The new diagram is extended by classic Voronoi diagrams, and the discrete construction method is introduced.

Compared with the grid-based methods, the computation complexity geometry-based methods can be greatly reduced, and they can deal with the area and obstacles with complex shape. However, whether it’s grid-based method or geometry-based method, they are almost based on the coverage of WSN or the improved coverage modal. As for DASNs, coverage is different from that of passive sensor network and independent active sensor network in that the ability to detect obstacles is determined by both the deployment of visible actuators and sensors, as well physical medium and the environment layouts [8].

To the best of our knowledge, we are the first one to study sensor placement problem to achieve minimum exposure which quantifies dimension of obstacles that cannot be detected by an arrangement of actuators/sensors considering both the metrics affecting detectability of DASNs including the placement of visible actuators and sensors, as well physical medium and the environment layouts. It is deployment-centric and is independent of detailed characteristics of obstacles.

III. PROBLEM MODELS AND PREPARATORY WORK

It is assumed that actuator and sensor devices are placed in a bounded two-dimensional area. If the path between a sensor and an actuator is accessible, the sensor can detect signals from the actuator. Reactions on external and internal boundaries may create non-line-of-sight paths. Such non-line-of-sight paths can be broken into a collection of line segments and treated individually in a similar fashion as line-of-sight paths between sensors and actuators. Known internal and
external boundaries can also be represented approximately by some line segments. Visibility between actuators and sensors is restricted by their distance due to signal attenuation in the medium. Given the location of sensors and actuators, layout and propagation properties of the medium, DASN can be modeled as the arrangement of line segments. The inside of line segments and their endpoints (corresponding to sensors and actuators) are called sites [8]. It should be noted that in a general configuration, two line segments can intersect at one internal point.

The monitoring objects that the observer is interested in are also the sensing objects of WSNs. However, objects not only can destroy sensors and actuators, but also can block the transmission path between sensors and actuators thus the actuators get invisible to corresponding sensors. This is similar to the blocking communication between nodes, which is a harmful and effective attack behavior [42]. So objects have a great impact on the DASNs. We can apply a simple threshold based processing mechanism to the sensor to determine whether the path is blocked [8]. In this paper, considering the direction of path is complex to handle, we use the maximal inscribed circle to simulate the object to avoid the complexity of direction.

The detectability of DASNs is roughly similar to the concept of coverage in passive sensor networks. The coverage solution of passive sensor network aims at eliminating the coverage vulnerability that can not be detected by events in the network. Generally, it is assumed that the disk and area sensing coverage model is used for passive sensors. As a result, to ensure full coverage, asymptotic bounds should be derived for the critical density [43]. There are many algorithms which have been researched in [43] to select the minimum number of sensors to ensure a certain coverage. Coverage in DASNs is essentially different from that in passive sensor network. In DASNs, the ability to detect obstacles depends on the deployment of the visible actuators and sensors, and the layout of the physical media and environment. In [8], to quantify the dimension limitations in detectability of DASN, we introduce a notion called exposure, which is a network-centric metric. It is excerpted from [8] as follows:

**Definition 1 (Exposure):** Given an arrangement of line segments $S$ consisting of interiors of line segments connecting visible sensors and actuators, their endpoints, i.e., sensors/actuators, and boundaries of the field. The exposure is measured as the radius of the maximum disk that does not intersect with any line segment in $S$.

Fig. 1 illustrates the actuators and sensors placed and the resulting line segments, exposure after deployment. There are four sensors/actuators deployed in monitoring field. We have drawn all the disks as large as possible that do not intersect with any line segment. The radius (red line) of the maximum disk (shaded) among all disks is “exposure”. In a physical sense, exposure is the maximum dimension of obstacles that cannot be detected by an arrangement of sites. Sensor range $D$ is the maximum distance visible between a pair of unobstructed sensor and the actuator.

Based on the definition of exposure, we can describe the problem in this paper as follows:

**Problem 1 (Minimum Exposure Deployment):** Given $N$ sensors and actuators, a 2-D field with exterior and interior boundaries $B$, and sensing range $D$, the minimum exposure deployment problem concerns with the optimal locations of the sensors and actuators to minimize the exposure.

Suppose $S = \{s_1, s_2, \cdots, s_N\}$ as the set of $N$ sensors and actuators. Divide monitoring field $B$ into cell grids. When $N$ sensors and actuators deployed in $B$, set $A = \{(x_1, y_1), (x_2, y_2), \cdots, (x_N, y_N)\}$ as the set of locations of $S$. One of the deployments of $S$ can get the minimal exposure.

$$A^* = \arg \min_{A \in B} \text{expo}(S, B, D, A),$$

where $\text{expo}$ is the exposure of sensors deployment (Fig. 1), namely, is the radius of the maximum disk in monitoring field with sensors distributed. $A^*$ is the optimal sensor deployment with minimum exposure.

There are two main challenges in achieving the minimum exposure deployment. One is that the interaction between sensors/actuators actually has a global impact. A change in sensor position will cause all line segments between the sensor and other visible actuators to change. The other is that external and internal boundaries add complexity to the deployment. In [44], the minimum exposure deployment problem has been proven NP-hard by us. This requires designing a heuristic solution that can approach the best solution within polynomials.

**IV. SENSOR DEPLOYMENT ALGORITHM**

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy [45], [46], inspired by social behavior of bird flocking or fish schooling. PSO shares many similarities with evolutionary computation techniques. The system is initialized with a population of random solutions and searches
for optimal solution by updating generations, but PSO has no evolution operators such as crossover and mutation in GA. In PSO, the potential solutions called particles. All particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles. PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two “best” values. One is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called pbest. The other “best” value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called gbest. In past several years, PSO and discrete binary particle swarm optimization (DPSO) have been successfully applied in many research and application areas [47], [48]. It is demonstrated that they get better results in a faster, cheaper way, and with fewer parameters to adjust than other methods. The key technique to solve the practical problems by using DPSO is to seek the suitable coding expression of particle for the problem space as well as the fitness function. The problem-specific domain knowledge and constraints should be incorporated into the algorithm to obtain the optimal solution and improve the convergence rate of the algorithm.

**Algorithm 1 Faiw-DPSO Algorithm Applied in Sensor Deployment**

**Input**: surveillance field boundary, the number of sensors \( N \), the number of iterations \( t_{max} \);

**Output**: the coordinate sensors in the field;

\[ x_i(t) \leftarrow \text{generate the initial particles}, 1 \leq i \leq n, t = 0; \]

\[ V_i(t) = 0; \]

\[ \text{exp}(i, t) \leftarrow \text{exposure}(x_i(t)); I^* \text{compute the exposure for each particle}; \]

\[ F_i = \text{fitness}(\text{exp}(i, t)); I^* \text{compute the fitness of each particle}; \]

\[ F^* = \max(F_i(t)); I^* \text{choose the max value}; \]

Set the pbest \( P_i = x_i(t) \) and its fitness \( F_i = F_i(t); \)

Set the gbest \( P_g = x^*(t) \), with the max fitness \( F^* \);

\[ \text{while } t \leq t_{max} \text{ do} \]

\[ x_i(t + 1) \leftarrow \text{all particles fly to new legitimate positions}; \]

\[ \text{exp}(i, t + 1) \leftarrow \text{exposure}(x_i(t + 1)); \]

\[ F_i(t + 1) \leftarrow \text{fitness}(\text{exp}(i, t + 1)); \]

if \( (F_i(t + 1) > F_i) \) then

\[ P_i = x_i(t + 1), \]

\[ F_i = F_i(t + 1), \]

\[ I^*(t) = +1; \]

else

\[ I^*(t) = -1; \]

if \( (F_i(t + 1) > F^*) \) then

\[ P_g = x_i(t + 1), \]

\[ F^* = F_i(t + 1); \]

\[ t = t + 1; \]

**B. FLYING OF PARTICLES**

At each iteration, all the particles move in the problem space to find the global optima. The velocity and position of each particle is adjusted by the following formulas:

\[ v_{id}(t + 1) = w \cdot v_{id}(t) + c_1 \cdot r_1 \cdot (P_{id} - x_{id}(t)) + c_2 \cdot r_2 \cdot (P_g - x_{id}(t)), \]

\[ x_{id}(t + 1) = \begin{cases} 1, & \text{if } \rho_{id}(t + 1) < \text{sigmoid}(v_{id}(t + 1)), \\ 0, & \text{otherwise}. \end{cases} \]

where variable \( i \) denotes the \( i \)-th particle in the swarm; \( t \) represents the current iteration number; \( d \) is the \( d \)-th dimensional value of the vector, \( 1 \leq d \leq m \cdot n; v_i \) is the velocity vector of the \( i \)-th particle; \( P_i \) is the position vector of the \( i \)-th particle; \( x_i \) is the individual best position that the \( i \)-th particle had reached; \( P_g \) is the global best position that all the particles had reached; \( w \) is called inertia weight; \( c_1 \) and \( c_2 \) are two constants, which are called cognitive confidence coefficients; \( r_1 \) and \( r_2 \) are random value between 0 and 1; \( \rho_i \) is a quasi-random value selected from a uniform distribution in \([0.0, 1.0]. \) \text{sigmoid}(v) = 1 / (1 + \exp(-v)). \) Furthermore, the largest moving velocity is restricted by \( v_{max} \), that is \( |v_{id}(t + 1)| \leq v_{max} \), which limits the ultimate probability that

**A. BINARY PARTICLE ENCODING IN TWO-DIMENSIONAL SPACE**

In this paper, binary inputs from sensors are assumed indicating whether the propagation path from an actuator and a sensor is obstructed. As Fig. 2(b) shows, ‘1’ reading indicates the target is present and ‘0’ otherwise. Binary sensing is attractive due to its low cost and power consumption. In contrast to passive sensing where the detection of targets is generally determined by the proximity of targets to sensors, in DASNs, both the proximity of targets to sensor-actuator pairs as well as the dimension of targets affect the likelihood of detection. We introduced a particle coding named planar binary particle coding to illustrate the sensor deployment. As shown in Fig. 2, each particle is a binary matrix of \( u \times v \) grids. Every grid point \((i, j)\) can only place one sensor denoted by “1” if it does exist there. There should be \( N \) elements “1” in the matrix since the number of sensors is \( N \). Therefore, we set the following constant which need to be maintained by particle flying.

**Sensor Number Constant:** There should be \( N \) marks of 1 in each legitimate particle.

The planar binary particle coding method shown in Fig. 2 is superior to other types of encoding because it is especially suitable for sensor deployment with two-dimensional attributes. It will be demonstrated in following sections that the coding method shows great flexibility in incorporating geometric knowledge to the algorithm.
bit $x_{id}(t+1)$ will take on a binary value. A smaller $v_{max}$ will allow a higher mutation rate.

Suitable selection of inertia weight $w$ in (2) provides a balance between global and local exploration and exploitation, and results in less iterations required to find a sufficient optimal solution. In order to improve the convergence speed and global searching ability of algorithm, we design a feedback-based adjustment mechanism on inertia weight. As originally developed, the inertia weight $w$ is set according to the following equation:

$$w = \frac{1}{2} (w_{max} + w_{min}) + I(\cdot) \cdot \frac{1}{2 \cdot I_{max}} (w_{max} - w_{min}) \cdot t,$$  \hspace{1cm} (4)$$

where $I_{max}$ is the maximum iteration number, $w_{max}$ is the maximum inertia weight, $w_{min}$ is the minimum inertia weight. $I(\cdot)$ is the feedback-based adjustment coefficient which initialized as 1. When $I(\cdot) = 1$, it can be seen from (4) that the inertia weight $w$ increases linearly within $[\frac{1}{2} (w_{min} + w_{max}), w_{max}]$, accordingly, the optimal solution in (5) continues to evolve towards the original direction. On the contrary, when $I(\cdot) = -1$, the algorithm tends to explore new solutions as the inertia weight $w$ decreases within $[w_{min}, \frac{1}{2} (w_{min} + w_{max})]$ correspondingly. Thus the feedback-based adjustment mechanism can improve the convergence speed of algorithm and avoid the algorithm falling into local optimum. The specific adjustment strategy of $w$ will be determined by the effect of the solution searched, which is shown in (6). Since the optimal range for a linear change strategy on inertia weight is from 0.4 to 0.9 \cite{49}, the $w_{min}$ in (4) is 0.4, the $w_{max}$ is 0.9.

However, the updated particles may violate the Sensor Number Constant. In fact, the number of elements 1 in the resulting matrices may be smaller or larger than $N$ as shown in Fig. 3(b) and Fig. 4(b). To satisfy the constant, we revise the updated particles in following steps:

Given the particle $O$, with the elements $o_{ij}$.

1. If $\sum o_{ij} < N$, calculate the current exposure. Let the center of the maximal disk be $(x, y)$. An additional sensor is included at location $(x, y)$ and $o_{xy} = 1$ (Fig. 3(c));

2. If $\sum o_{ij} > N$,

   $$o^*_{ij} = \arg \min_{o_{ij} = 1} \left\{ \sum_{o_{uv} = 1, u \neq i, v \neq j} D(o_{ij}, o_{uv}) \right\},$$

   where $D(o_{ij}, o_{uv}) = \| o_{ij} - o_{uv} \|$ is the Euclidean distance between $o_{ij}$ and $o_{uv}$, then set $o^*_{ij}$ to 0 (Fig. 4(c));

3. Repeat step 1, until $\sum o_{ij} = N$.

In step 1, an additional sensor is put in the field. Intuitively, if the sensor is placed at the center of the maximal disk, we can effectively reduce the exposure value...
of the deployment. In step (2), a sensor is removed to construct a legitimate individual. Instead of stochastically deciding which sensor to be removed, we find the sensor $o^*_i$ that is nearest to the center of the sensors, and remove this sensor as $o^*_i$ is unlikely to contribute to the exposure. This revision process proceeds in an incremental manner by incorporating geometric knowledge to reduce the exposure. By the end of the procedure, former legitimate particles acted upon by flying (moving) produce new legitimate particles satisfying the Sensor Number Constant.

C. FITNESS FUNCTION AND FEEDBACK-BASED ADJUSTMENT MECHANISM ON INERTIA WEIGHT

The fitness function plays a decisive role in the DPSO algorithm. Generally, the fitness function is used to evaluate the quality of all the proposed solutions to the problem in the current particle swarm. The fitness function evaluates how good a single solution in a particle swarm is. It can be clearly seen from the above content that one obvious fitness criterion of the deployment problem is the exposure. If only the factor of exposure is considered, it is easy to discover two deployments with the same exposure values and among that there is one with more clustered deployment of sensors. If the sensors deployment is too clustered, it will bring other huge loopholes to the networks. Therefore, the criterion we choose a fitness function is to minimize the exposure and deploy sensors evenly as far as possible in the field within the constraints of boundary.

Definition 1 (Fitness Function): The fitness of $O$ is defined as follows:

$$F(O) = k - [\rho \cdot R(O) + (1 - \rho) \cdot \sigma(O)]$$  \hspace{1cm} (5)

where $R(O) = \max_{i=1,2,...,m} \{r_i\}$ is the radius of exposure; $\sigma(O) = \sqrt{\frac{1}{m} \sum_{i=1}^{m} (r_i - \bar{r})^2}$ is the mean square error of all disk radius. $\rho \in [0, 1]$, $\rho$ is a tunable parameter that controls the trade-off between the two criterions (i.e., exposure vs. even distribution). $K$ is a constant positive value big enough. Clearly, the bigger the $F$, the better the deployment.

The particle with the largest $F$ corresponding to an efficient sensor deployment is the gbest $P_g$, which will broadcast its information to the other particles. All particles fly through the problem space by following the current optimum particle and their individual history information.

Since the fitness function is constructed, the fitness function value $F(O)_t$ will produced at $t$th iteration in running period. We set the feedback-based adjustment coefficient $I(\cdot)$:

$$I(\cdot) = \begin{cases} +1, & F(O)_t > F(O)_{t-1} \\ -1, & F(O)_t \leq F(O)_{t-1}, \end{cases}$$  \hspace{1cm} (6)

where $F(O)_t$ represents the fitness function value in $t$th iteration. So the feedback-based adjustment coefficient is updated at the end of this iteration and used in next iteration. From (6), when the optimal solution is still evolving in the running period of algorithm, $I(\cdot) = +1$, i.e., the adjustment of the inertia weight $w$ is positive feedback. Thus $w$ increases, the optimal solution continues to evolve in the original direction. Conversely, when the optimal solution of the algorithm is not improved even decreased obviously, $I(\cdot) = -1$, i.e., the feedback is negative. The inertia weight $w$ is reduced, so the probability of previous solution is reduced, and the algorithm tends to explore new solutions and improve the convergence speed. So, $w$ changes linearly according to quality of solution during a run, which does well to the convergence of the algorithm.

D. SKETCH OF THE SENSOR DEPLOYMENT ALGORITHM BASED ON FAIW-DPSO

Based on above demonstrations, the sensor deployment algorithm using Faiw-DPSO is presented as Algorithm 1.

V. EVALUATION

The proposed Faiw-DPSO algorithm has been implemented in C. The exposure of DASNs is computed by CGAL...
In addition to the proposed Faiw-DPSO algorithm in this paper, four baseline methods including the original greedy algorithm, GA, Gibbs sampler, and the basic DPSO algorithm were compared over exposure and running time.

- **Greedy algorithm (greedy)**, which iteratively deploys sensors in monitoring field, where every sensor is placed at the center of the maximal disk with the exposure.

- **Genetic algorithm (GA)**, where to deploy sensors and minimize the exposure of DASNs similarly. The parameter settings of GA have been researched in [16]. The results in Fig. 8 in [16] show that when \(p_c\) is 0.90 and \(p_m\) is 0.02, the optimal exposure and convergence speed are obtained. Similar observations can be obtained from experiments with different numbers of sensors [16]. The population size \(M\) also achieves the best balance between performance optimization and convergence time minimization through experiments. All the parameter settings can be seen in Table 1.

- **Gibbs sampler**, which aims at deploying sensors based on the exponential cooling schedule to converge faster to optimal solution in [17]. The main user-defined parameters of Gibbs sampler are the initial temperature \(T_0\) and the coefficient \(\alpha\) in exponential cooling schedule shown as \(T_n = T_0 \cdot \alpha^n\). \(\alpha\) is usually taken to be in the range 0.95-0.99, and the specific optimal values of \(\alpha\) for different number of sensors are set in [17]. Here we use it directly in Table 1.

- **The basic DPSO algorithm**, where is applied in sensor deployment directly without additional improvements. An experimental design shown below is used to find the best combination of user-defined parameters.

### TABLE 1. Experiment parameter settings in different algorithms.

| number of sensors \(N\) | GA | Gibbs sampler | DPSO/Faiw-DPSO |
|-------------------------|------------------|------------------|-----------------|
|                         | Population size | Maximum iteration | \(p_c\) | \(p_m\) | \(\rho\) | \(T_0\) | \(\alpha\) | Particle swarm size | Maximum iteration | \(w\) | \(c_1\) | \(c_2\) |
| 4                       | 30              | 100             | 0.9 | 0.02 | 0.95 | 0.1 | 0.95 | 50 | 80 | 0.9 | 1.494 | 2 |
| 8                       |                 |                 |     |     |     |     |     |     |     |     |     |     |
| 16                      |                 |                 |     |     |     |     |     |     |     |     |     |     |
| 32                      |                 |                 |     |     |     |     |     |     |     |     |     |     |

### TABLE 2. Experiment results in regular field.

| Items                  | Methods      | Values                      |
|------------------------|--------------|-----------------------------|
|                       |              | 4 sensors | 8 sensors | 16 sensors | 32 sensors |
| Best exposure          | Faiw-DPSO    | 25.32     | 20.95     | 9.75       | 9.28       |
|                        | DPSO         | 25.98     | 21.94     | 10.88      | 9.86       |
|                        | GA           | 27.31     | 25.89     | 14.07      | 12.14      |
|                        | Gibbs sampler| 26.63     | 24.04     | 14.85      | 12.47      |
|                        | greedy       | 35.79     | 30.60     | 15.31      | 14.32      |
| Running time(s)        | Faiw-DPSO    | 13.86     | 27.47     | 48.25      | 66.36      |
|                        | DPSO         | 14.32     | 31.83     | 54.20      | 74.86      |
|                        | GA           | 21.12     | 38.47     | 64.21      | 89.09      |
|                        | Gibbs sampler| 18.34     | 37.95     | 68.36      | 95.23      |
|                        | greedy       | 2.34      | 3.46      | 7.07       | 13.12      |
| Average exposure       | Faiw-DPSO    | 26.43     | 21.45     | 10.43      | 9.88       |
|                        | DPSO         | 27.79     | 22.76     | 11.88      | 10.73      |
|                        | GA           | 29.09     | 26.45     | 14.98      | 12.63      |
|                        | Gibbs sampler| 28.20     | 23.62     | 16.83      | 13.79      |

### TABLE 3. Reasonable combination of four DPSO/Faiw-DPSO parameters and the corresponding result in exposure minimization.

| Number | \(w\) | \(c_1\) | \(c_2\) | \(M\) | Minimum exposure | Running time(s) |
|--------|-------|--------|--------|------|----------------|----------------|
| 1      | 0.2   | 0.9    | 0.9    | 10   | 15.01          | 89.79          |
| 2      | 0.2   | 1.494  | 1.494  | 30   | 12.60          | 69.45          |
| 3      | 0.2   | 2      | 2      | 50   | 11.51          | 66.34          |
| 4      | 0.6   | 0.9    | 1.494  | 50   | 13.82          | 67.37          |
| 5      | 0.6   | 1.494  | 2      | 10   | 11.12          | 76.32          |
| 6      | 0.6   | 2      | 0.9    | 30   | 12.37          | 92.23          |
| 7      | 0.9   | 0.9    | 2      | 30   | 10.68          | 72.74          |
| 8      | 0.9   | 1.494  | 0.9    | 50   | 9.34           | 66.93          |
| 9      | 0.9   | 2      | 1.494  | 10   | 9.06           | 66.73          |

**A. SENSITIVITY ANALYSIS OF USER-DEFINED PARAMETERS OF DPSO**

In order to optimize the parameter settings of the proposed DPSO and Faiw-DPSO algorithms, we use the Taguchi’s experimental design method in [52], which aims at finding the DPSO algorithm parameters with the minimum running time and the best robustness. Four parameters (inertia weight \(w\), two learning factors \(c_1\), \(c_2\) and population size \(M\)) that affect DPSO algorithm are selected as control factors. Considering the optimization method of experimental design, each parameter takes three levels: three levels for \(w\) ∈ {0.2, 0.6, 0.9}; three levels for \(c_1\) ∈ {0.9, 1.494, 2} and \(c_2\) ∈ {0.9, 1.494, 2} [53]; three levels for \(M\) ∈ {10, 30, 50} [54]. Because there are four parameters in the experiment and each parameter has three levels, the orthogonal test table of \(L_9(3^4)\) that contains only 9 experiments is selected for the experimental study. Compared with the full-factorial analysis that needs \(3^4 = 81\) experiments, Taguchi’s method greatly reduced complexity. The specific experimental scheme shown as Table 3.
The experiment is based on the deployment of 32 sensors. In this paper, the minimum exposure and running time of the optimal solution are used as the signal-to-noise ratio (SNR) of Taguchi’s method to evaluate the performance of DPSO.

\[
S/N_{\text{exposure}} = -10 \cdot \log\left(\frac{1}{n} \sum_{i=1}^{n} x_i^2\right), \quad (7)
\]

\[
S/N_{\text{time}} = -10 \cdot \log\left(\frac{1}{n} \sum_{i=1}^{n} y_i^2\right), \quad (8)
\]

where \(x_i\), \(y_i\) represents the output characteristics of the system, i.e., the minimum exposure and running time. And \(n\) is the number of levels divided in Taguchi’s method, i.e., \(n = \{1, 2, 3\}\). The experimental results including minimum exposure and running time of 9 sets of tests are also shown in Table 3. Put the minimum exposure of each group of tests into (7) to get \(S/N_{\text{exposure}}\), put the running time into (8) to get \(S/N_{\text{time}}\), and then add the two SNRs to get the required SNR.

As a result, we obtain the optimal combination of parameters: \(w = 0.9, c_1 = 1.494, c_2 = 2, M = 50\). As for Faiw-DPSO algorithm, the inertia weight is not constant. It changes as algorithm evolved. From (4) and its analysis, we have got \(w_{\text{min}} = 0.4, w_{\text{max}} = 0.9\).

### B. EVALUATION COMPARISON

In the first group of experiments, 4 to 32 sensors are placed in a 200 × 200 regular rectangular monitoring field. In the second group, 6 sensors are placed in the H-shaped region which is irregular. In each group of experiments, the revealed results are all the average values of 50 runs. All experimental programs are run on a Linux server with Intel Core i5 CPUs @ 2.70GHz and 8GB of memory and the running time was measured.

#### 1) REGULAR MONITORING FIELD

The parameter settings of five methods discussed in this paper are shown in Table 1. And the major experimental results are summarized in Table 2. Fig. 5 illustrates the convergence performance of five different algorithms applied in 4, 8, 16, and 32 sensors respectively. Since greedy is executed only once, it converges in only one iteration as shown in the dashed black line in the Fig. 5. The other lines in the picture depict the evolution of other four algorithms, which are shown as the average value of best exposures over 50 random realizations. And we can see that the best exposure of Faiw-DPSO (solid red line) are almost smaller than other heuristic algorithms especially the basic DPSO algorithm at each iteration.
As shown in Fig. 5, with 4, 8, 16, and 32 sensors in the field, the convergence rate of Faiw-DPSO is quite faster than other algorithms. Specifically, the running time of these algorithms shown in Table 2 illustrates the run-time performance of Faiw-DPSO is superior to others too. Furthermore, we can see that with sensors in the regular field, the proposed Faiw-DPSO algorithm can reduce the best exposure by 74% compared with greedy from Table 2. Meanwhile, looking at the curves of DPSO and Faiw-DPSO separately, we find that the red solid line (Faiw-DPSO) is almost under the red dashed line (DPSO), and the red solid line reaches the optimal value faster than the red dashed line. This shows that the feedback-based adjustment mechanism on inertia weight does improve the global optimization ability and
convergence speed of the basic DPSO algorithm. All the results shown above prove that the sensor deployment of Faiw-DPSO is superior to GA, Gibbs sampler as well as greedy.

From the four groups of experiments in Fig. 5, we choose the group with the largest number of sensors, that is, 32, and give their optimal deployment results shown in Fig. 6. As shown in Fig. 6, the proposed Faiw-DPSO algorithm does get the smaller exposure valued 9.28 than other algorithms when there are 32 sensors. Furthermore, from the view of the shape formed of sensor deployment, the more evenly sensors deployed, the smaller exposure obtained. The Faiw-DPSO algorithm dose divide the field more evenly, thus reduces the exposure obviously.

2) IRREGULAR MONITORING FIELD

In irregular monitoring field, certain locations inside are not accessible. Grid points corresponding to particles are marked as illegal. Fig. 7 shows that six sensors are deployed by five algorithms respectively in the H-shaped irregular field model that is a double beam structure. We set the sensing range to 250. Only if the line segments between the sensors are shorter than 250 and do not cross the “illegal” particle, then they exist. The optimal sensors deployment result in an H-shaped irregular monitoring field shows that the Faiw-DPSO algorithm can do to minimize exposure. By comparing the subfigures in Fig. 7, it can be concluded that the exposure of sensor deployment by Faiw-DPSO algorithm is smaller than that of others. Fig. 8 is the evolutionary curves of the proposed...
algorithm applied in irregular monitoring field. It illustrates that the average best exposure over 200 random realizations using Faiw-DPSO is almost minimum among all benchmark methods.

VI. CONCLUSION

With the development of sensing technology, DASNs is playing an increasingly significant role with its high efficiency and reliability. The deployment of sensors in DASNs is the vital part. In this paper, we proposed a sensor deployment method based on Faiw-DPSO in DASNs. The combination of geometric knowledge can significantly improve the convergence speed. To take both the metrics affecting detectability of DASNs including the placement of visible actuators and sensors, as well physical medium and the environment layouts into account, we set the fitness function of Faiw-DPSO algorithm which can minimize exposure and deploy the sensors more evenly in the field. Furthermore, the feedback-based adjustment mechanism on inertia weight, in which inertia weight factor is adjusted linearly and dynamically according to searching effectiveness of algorithm, does improve the convergence speed and global searching ability of algorithm. It can be demonstrated from implemented simulations that the proposed algorithm outperforms an original greedy algorithm by up to 74% and performs better than other related algorithms. It is an effective heuristic algorithm to achieve low exposure, high scalability and fast convergence. Besides, experimental data and images also show that the algorithm is robust, efficient and self-adaptive meanwhile in regular and irregular monitoring field. Finally, our next work is to start to improve the complexity of the algorithm in this paper and consider the optimization of sensor deployment under three-dimensional condition.

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