An Efficient Approach to the k-Strong Barrier Coverage Problem Under the Probabilistic Sensing Model in Wireless Multimedia Sensor Networks

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Abstract. Barrier coverage (BC) is a potential coverage model in wireless multimedia sensor networks (WMSNs) for applications such as intrusion detection and border surveillance. This model necessitates a chain of sensors positioned across the deployment region with overlapping sensing fields. However, achieving k-strong barrier coverage following the initial random sensor deployment poses significant challenges. BC holes frequently emerge within the sensing fields, even in high-density sensor. Previous research primarily focused on addressing the problem of constructing k-strong barrier coverage under a Boolean disk or a sector coverage model. This approach leads to inaccurate assessments of barrier coverage quality. To address the limitation, this paper presents an efficient scheme for achieving k-strong barrier coverage in heterogeneous WMSNs (HeWMSNs) using the minimum number of mobile sensors, while employing a probabilistic sector coverage model. By leveraging the proposed probabilistic sector sensing coverage model, we formulate the problem of attaining k-strong barrier coverage in HeWMSNs as a combinatorial optimization problem called KSB-HeWMSN. Subsequently, an efficient evolutionary algorithm is developed to tackle this problem. Through both analytical analysis and experimental evaluations conducted on multiple instances, the proposed algorithm demonstrates its suitability for the KSB-HeWMSN problem and its superior solution quality compared to previous approaches.

Keywords: Heterogeneous wireless multimedia sensor networks · barrier coverage · k-strong barrier coverage · evolutionary algorithm

1 Introduction

Barrier coverage (BC) in wireless Internet of Things sensor networks is garnering more and more attention from academia to industry all over the world [9,21]. BC is a well-known appropriate coverage model in wireless sensor networks (WSNs) for intrusion

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detection and border surveillance applications that aim to detect intruders attempting to penetrate protected areas [1, 11]. BC is a sensing region made up of nodes or sensor clusters connected over the entire deployment zone, creating one or more sensor barriers that act as a "virtual fence" to detect intrusions. In contrast to full coverage, barrier coverage can effectively detect intruders with fewer sensor nodes since it does not have to detect a moving intruder along every point of his trajectory in the monitored area. BC can be sufficient if the object can be detected by at least k distinct sensors before it penetrates through the sensor field. This requires a WSN providing k strong barrier coverage over a region of interest (ROI) such that any crossing path intersects with the sensing areas of k distinct sensors [18]. Sensor nodes, however, can typically be dispersed or dropped randomly in large numbers over a vast inaccessible, or hostile territory. It is challenging to achieve strong barrier coverage after an initial random deployment of sensors since their locations cannot be predicted or controlled. Therefore, optimizing WSNs deployment costs or the minimization of sensor count while guaranteeing robust barrier coverage in extensive geographical areas assumes paramount significance.

Today, heterogeneous wireless multimedia sensor networks (HeWMSNs) have drawn tremendous attention due to their potential impacts on scientific research and numerous attractive applications. Heterogeneous networks consist of sensors with different capabilities and therefore can bring benefits such as improving network performance, reliability of data transmission, prolonging network lifetime, decreasing the latency of data transportation, reducing the cost of developing network, etc. [12]. Wireless multimedia sensor networks (WMSNs) can significantly improve the sensing ability on environments and description ability of environmental events [16], with the development of various types of multimedia sensors, such as camera sensors, video sensors, etc. These sensors comply with the directional sensing model and can collect much richer information (images or video) than others with omni-directional sensing models. However, WMSNs have unique features of the directional sensing model, such as angle of view, working direction, and line of sight. These features have brought in new challenges such as the requirement for using more parameters to model the directional sensors and the increasing complexities of solving the k strong barrier coverage problem in WMSNs. Although prior research has extensively examined the challenge of achieving k strong barrier coverage in the directional sensing coverage model, a majority of these investigations have been predicated on several assumptions. Firstly, their prevalent utilization of Boolean sectors as the sensing coverage models for the sensors [8, 10, 13] has introduced inaccuracies in assessing the coverage quality along the barrier since every point within the sensor's sensing range is equally considered. Secondly, homogeneous sensor networks have been assumed in these studies. Lastly, the solutions proposed in the literature have ample room for quality enhancement.

As previously highlighted, it is of utmost importance to address the k strong barrier coverage problem in HWMSNs while simultaneously minimizing the sensor count. Furthermore, the introduction of a novel sensing coverage model that surpasses the constraints of the Boolean model assumes great significance. Consequently, in this study, we propose an efficient heuristic algorithm that aims to minimize the required quantity of mobile sensors while attaining k-strong barriers within HeWMSN, achieved by utilizing a probabilistic sector sensing model.

The main contributions of this paper are as follows:

- Formulate the k-strong barrier coverage problem in HeWMSNs under the proposed probabilistic sector sensing model into a combinatorial optimization problem known as KSB-HeWMSN.
- Proffer an elite evolutionary algorithm called KSB-EA with a new individual representation, suitable crossover and mutation operators for solving KSB-HeWMSN.
- Conduct various experimental scenarios to examine the proposed algorithms and compare the proposed method to state-of-the-art.

The rest of the paper is organized as follows. Section 2 presents Related works. Preliminaries and formulation for the KSB-HeWMSN problem are discussed in Sect. 3. Section 4 introduces the proposed algorithms. Experimental results are given and analyzed in Sect. 5. Finally, the conclusions of the paper are presented in Sect. 6.

2 Related Works

BC problems in WSNs can be classified into weak barrier coverage and strong barrier coverage [21]. Regarding weak barrier coverage, the minimal exposed path is thought to be the worst-case coverage, which is a weak barrier coverage. Recently, Binh et al. have investigated this field such as [3,4,14,19]. The minimal exposure path (MEP) is a typical path of the worst coverage in WSNs. The MEP problem aims to find a path where an intruder can penetrate through a region with the lowest probability of being detected and was proven an NP-Hard problem [7], and Binh et al. have proposed efficient heuristic algorithms for solving it with different scenarios.

With reference to strong barrier coverage, algorithms for building barriers have been researched in various respects. Saipulla et al. in [15] studied how to deploy efficiently for barrier coverage in WSNs and established a tight lower bound for the existence of barrier coverage under line-based deployments. Recently, Ma et al. in [13] suggested precise algorithms for rotatable line-based deployed directional sensors to cover barriers. To determine the best sensor orientations for BC with the least amount of sensor deployment, the study offered two optimization models for the problem, one based on integer linear programming and the other based on mixed-integer linear programming. The suggested algorithms can achieve better coverage and use fewer sensors than existing techniques, according to simulation data.

Furthermore, Zhang et al. [22] also focused on the k-barrier coverage problem in omni-directional WSNs, which is then transformed into a global optimization problem. The authors proposed a heuristic algorithm, which was combined with particle swarm optimization and artificial immunity for solving the problem. The research of [17] focused the ways to improve barrier coverage by combining mobile sensors with a probabilistic sensing model. Most recently, Chen et al. in [8] described how to effectively leverage the rotational capabilities of fixed sensors and the mobility capabilities of mobile sensors to achieve k-barrier coverage in a randomly deployed hybrid visual sensor network. The study focused on three issues: minimizing the number of mobile sensors needed, reducing the overall moving distance, and solving the maximum number of strong barriers with deployed stationary and mobile sensors. To solve these issues, they developed a robust k-barrier coverage enhancing scheme (KCES) and a virtual barrier curve (VBC) model to translate the k-barrier construction issues into issues with repairing barrier gaps in k turns. These studies are the most relevant to ours. However, their proposed algorithms are not efficient because the quality of solutions and the computation time are still room for improvement.

In short, after delving into the related works to the problem of constructing k-strong barrier coverage in HeWMSNs while minimizing the requirement of mobile sensor nodes (referred to as the KSB-HeWMSN problem), we find out that this problem holds significant importance in both theoretical studies and practical applications, but it presents several intrinsic challenges that need to be addressed.

3 Preliminaries and Problem Formulation

3.1 Preliminaries

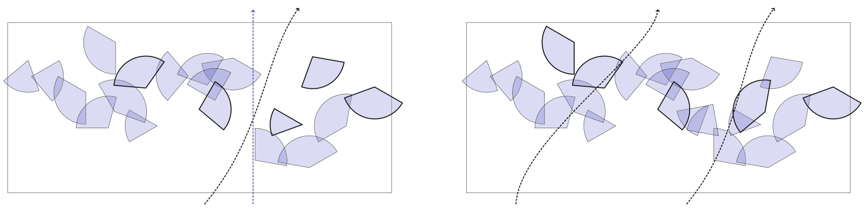
The Probabilistic Sector Coverage Model

A multimedia sensor s can be characterized by an 8-tuple $\langle\, x, y, r_1, r_2, \alpha, \beta, \gamma_1, \gamma_2 \rangle$, where (x, y) is the position P of the sensor node; r_1 and r_2 respectively denotes an uncertain and a maximum sensing radius of the sensor; α is half of the sensing angle; $\beta = \angle(\overrightarrow{Wd}, \overrightarrow{Px})$ is the orientation angle, where $\overrightarrow{Px}$ is the horizontal axis and $\overrightarrow{Wd}$ is the unit vector whose direction coincides with the bisector of the sensing angle; and γ_1, γ_2 are parameters set according to the physical properties of the sensor. The coverage function of the probabilistic sector model is given as

$$f(s, O) = \begin{cases} 1 & \text{if } d \leq r_1 \text{ and } d \cdot \cos(\alpha) \leq \overrightarrow{PO} \cdot \overrightarrow{Wd}, \\ \exp(-\gamma_1 \cdot \delta^{\gamma_2}) & \text{if } r_1 < d \leq r_2 \text{ and } d \cdot \cos(\alpha) \leq \overrightarrow{PO} \cdot \overrightarrow{Wd}, \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

demonstrating the probability of object O detected by sensor s, where $\overrightarrow{PO}$ is the vector from sensor's position P to object O, $d = \left|\overrightarrow{PO}\right|, \delta = d - r_1$.

Strong Barrier with Desired Probability $\mathcal{P}$



(a) The network can provide a weak barrier coverage in Ω;

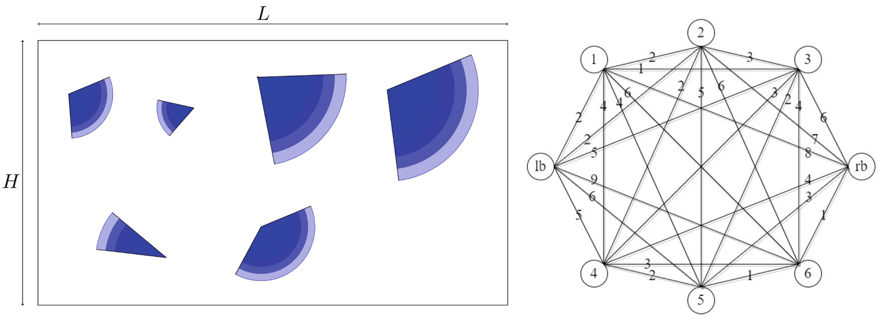
(b) The network can provide a strong barrier coverage in Ω

Fig. 1. Illustration of the two types of barrier coverage on the region of interest Ω

A strong barrier with desired probability $\mathcal{P}$ is a set of sensors ensuring that every intruder's path is detected by that set with a probability greater than or equal to $\mathcal{P}$. A HeWMSN deployed over a RoI is said to achieve k-strong barrier if there exists a set of k disjoint strong barriers with desired probability $\mathcal{P}$ (Fig. 1).

Weighted Barrier Graph

Based on the above definitions, a weight barrier graph (WBG) is defined as a set $\langle \mathcal{V}, \mathcal{E}, \mathcal{W} \rangle$, where $\mathcal{V} = \{\mathsf{lb}, v_1, v_2, ..., v_n, \mathsf{rb}\}$ is the set of vertices representing n sensor nodes and two boundaries of the RoI, i.e. the left boundary $\mathsf{lb} \equiv v_0$ and the right boundary $\mathsf{rb} \equiv v_{n+1}$; $\mathcal{E} = \{(v_i, v_j) | i = \overline{0, n}; j = \overline{1, n+1}\}$ is the set of edges; and $\mathcal{W}$ is the weight mapping, where the edge $e(v_i, v_j)$ is associated with a weight denoted as $\mathbf{w}(v_i, v_j)$, representing the minimum number of mobile sensors required to connect vertices v_i and v_j. Figure 2a depicts a HeWMSN including 6 sensors deployed randomly in a ROI and Fig. 2b illustrates the WBG constructed from that network.



(a) A HeWMSN deployed in the RoI.

(b) The WBG built from the network.

Fig. 2. Illustration of transforming from HeWMSN to WBG

3.2 Problem Formulation

Given a region of interest Ω with the width W and the height H, where n heterogeneous multimedia sensors are randomly deployed. The objective of the KSB-HeWMSN problem is to construct k-strong barrier coverage while minimizing the number of required mobile sensors to fill the gap among initial static sensors. The KSB-HeWMSN's input and output can be formulated more precisely as follows:

Input:

- L, H: the length and the height of the RoI Ω
- n: the number of multimedia sensors
- $\mathcal{S} = \{s_i = (x_i, y_i, r_{1i}, r_{2i}, \alpha_i, \beta_i, \gamma_{1i}, \gamma_{2i}) | i \in 1...n\}$: set of multimedia sensors deployed in the RoI Ω.
- $r_{1m}, r_{2m}, \alpha_m, \gamma_{1m}, \gamma_{2m}$: the properties of mobile multimedia sensors

– k: the number of strong barriers, $k \leq n$
– $\mathcal{P}$: the desired probability, $0 < \mathcal{P} \leq 1$

Output: The minimum number of required mobile multimedia sensors.

Objective:

$$\underset{x_{p_i p_j l} \mid p_i, p_j \in \mathcal{V}, l = \overline{1,k}}{\text{minimize}} \quad \mathsf{N_m} = \sum_{l=1}^{k} \sum_{(p_i,p_j) \in \mathcal{E}} \mathbf{w}(p_i, p_j) x_{p_i p_j l} \tag{2a}$$

subject to

$$x_{p_i p_j l} \in \{0, 1\} \quad \forall p_i, p_j \in \mathcal{V}, l \in \{1, 2, \ldots, k\}, \tag{2b}$$

$$\sum_{p_j \in \mathcal{V}; l = \overline{1,k}} x_{p_0 p_j l} = \sum_{p_i \in \mathcal{V}; l = \overline{1,k}} x_{p_i p_{n+1} l} = k, \tag{2c}$$

$$\sum_{p_i \in \mathcal{V}; l = \overline{1,k}} x_{p_i p_j l} = \sum_{p_m \in \mathcal{V}; l = \overline{1,k}} x_{p_j p_m l} \leq 1 \quad \forall p_j \in \mathcal{V} \backslash \{\mathsf{lb}, \mathsf{rb}\} \tag{2d}$$

where $\mathcal{V}$ is the set of vertices, $\mathcal{E}$ is the set of edges of the WBG; the variables $x_{p_i p_j l}$, with $p_i, p_j \in \mathcal{V}, l = \overline{1,k}$ decide whether the edge (p_i, p_j) is on the j-barrier or not:

$$x_{p_i p_j l} = \begin{cases} 1, & \text{if the edge } (p_i, p_j) \text{ is on the } j\text{-barrier,} \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

The objective function $\mathsf{N_m}$ in (2) formulates the number of required mobile sensors. The constraint (2b) describes the value domain of $x_{p_i p_j l}$, constraints (2c) ensure that there are exactly k barriers from lb to rb, and last constraint (2d) indicates that every sensor p_j appear in at most one barrier.

4 Proposed Algorithm

Evolutionary algorithms are a class of optimization algorithms inspired by the process of natural selection, which can surmount many optimization problems in various areas such as [2,4–6,14,19]. They iteratively evolve a population of candidate solutions through processes such as mutation, crossover, and selection to find optimal or near-optimal solutions to complex problems. This section describes an improved efficient evolution algorithm named KSB-EA to solve the KSB-HeWMSN problem with a flowchart demonstrated in Fig. 3. The pseudocode of the proposed algorithm is described in Algorithm 1.

4.1 Solution Representation and Population Initialization

In KSB-EA, an individual, which represents a feasible solution, is a permutation sequence including $n + k$ integer items, where n items assigned values from 1 to n represent n sensors, and k items assigned values as $n + 1$ represent k-strong barrier. Assume that these k items' indices are $a_1, \ldots, a_k$ and $a_0 = 0$, then each individual can be extracted to gain k strong barriers, with the i-th barrier formatted as

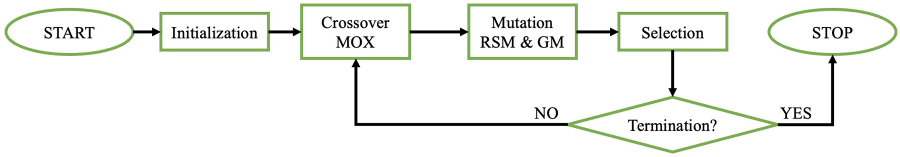


Fig. 3. Basic steps of the proposed algorithm KSB-EA.

Algorithm 1: KSB-EA

Input: The list of sensors $\mathcal{S}$, number of strong barriers k, the desired probability $\mathcal{P}$.
Parameters: Population size $\mathsf{Pop}_{\text{size}}$; crossover and mutation rates p_c, p_m; maximum number of generations $G_{\max}$
Output: The sub-optimal solution for the KSB-HeWMSN problem.

begin
    Initialization: Apply Algorithm 2
    Main loop: while *terminate condition not met* **do**
        Crossover and Mutation:
        foreach *individual* $\mathbf{ind}$ *in the population* **do**
            if $\mathcal{U}(0,1) < p_c$ **then**
                $\mathbf{ind}' \leftarrow$ a random individual in the population
                Add MOX$(\mathbf{ind}, \mathbf{ind}')$ to the population (Algorithm 3).
            end
            if $\mathcal{U}(0,1) < p_m$ **then**
                Add RSM$(\mathbf{ind})$ and GM$(\mathbf{ind})$ to the population (Algorithm 4 and 5).
            end
        end
        Evaluate and select individuals. (described in Section 4.3).
    end
    return the best individual of the population.
end

$(\mathsf{lb}, x_{a_{i-1}+1}, ..., x_{a_i-1}, \mathsf{rb})$. Figure 4 demonstrates an individual corresponding to a solution of the problem in Fig. 2a with 6 sensors ($n = 6$) and 3 barriers ($k = 3$). To ensure the diversity of the population, we use a random method to initialize which provides validity guarantees for the generated individuals described in Algorithm 2. The number of individuals is limited by the population size $\mathsf{Pop}_{\mathsf{size}}$.

4.2 Crossover and Mutation Operators

The crossover and mutation operators in evolutionary algorithms are pivotal components that significantly contribute to enhancing the diversity present within the population. In this paper, a new crossover operator referred to as MOX, which is a modified version of the traditional order crossover [20], is proposed and described in Algorithm 3. We also incorporate two types of mutation operators: Reverse Sequence Mutation (RSM) and Greedy Mutation (GM), whose details are shown in Algorithm 4 and 5 respectively. The GM draws inspiration from the note that when k is equal to 1, the

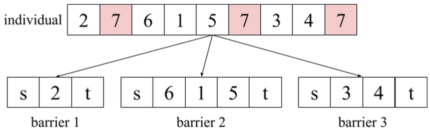


Fig. 4. An individual for the problem in Fig. 2a and the 3-strong barrier solution.

Algorithm 2: Initialization

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for $idx \leftarrow 1$ **to** $\mathsf{Pop}_{\mathsf{size}}$ **do**
    $c \leftarrow$ an array of $n+k$ elements; $x \leftarrow$ an array of $n+1$ zeros
    for $l \leftarrow 1$ **to** $n+k$ **do**
        do
            $c[l] \leftarrow \text{random}(1, n)$
        while $x[c[l]] \geq \max(c[l])$
        $x[c[l]]$++
    end
    Add c to population
end

Algorithm 3: MOX Crossover operator

Input: The parents individuals $p_1 = \{x_1, x_2, ..., x_{n+k}\}$ and $p_2 = \{y_1, y_2, ..., y_{n+k}\}$
Output: The offspring individual $c = \{c_1, c_2, ..., c_{n+k}\}$

$t \leftarrow \text{random}(1, k)$; Copy t random consecutive barriers from p_1 to c.
for $i \leftarrow 1$ **to** $n+k$ **do**
    if $t < k$ *and* $y_i = n+1$ **then**
        $c_i \leftarrow y_i; t \leftarrow t+1$
    else if $t < k$ *and* $y_i \notin p_1$ **then**
        $c_i \leftarrow y_i$
    end
end
return c

---

solution to this problem is simply the shortest path from lb to rb in the WBG. However, considering a barrier as a subgraph of the WBG, it is possible to achieve an improved barrier by finding the shortest path within it. The vertices that are not part of the barrier can be reused in subsequent barriers to construct more optimal barriers. The GM operates by utilizing a set called $list$ to store the vertices, and it employs the Dijkstra algorithm to find the shortest path on the WBG using the vertices in $list$ from lb to rb.

Algorithm 4: RSM operator

Input: The individual $c = \{c_1, c_2, ..., c_{n+k}\}$
Output: The mutated individual $c' = \{c'_1, c'_2, ..., c'_{n+k}\}$

$point1, point2 \leftarrow$ two random integers in $\overline{1, n+k}$ that $point2 > point1$; $c' \leftarrow c$
for $i \leftarrow point1$ **to** $point2$ **do**
  $c'_i \leftarrow c_{point2-i+1}$
end
return c

Algorithm 5: GM Operator

Input: The individual $c = \{c_1, c_2, ..., c_{n+k}\}$
Output: The mutated individual $c' = \{c'_1, c'_2, ..., c'_{n+k}\}$
$C' \leftarrow$ an empty set of barriers; $list \leftarrow \{\mathsf{lb}, \mathsf{rb}\}$;
for $l \leftarrow 1$ ***to*** $n + k$ **do**
  if $c[l] \neq n + 1$ **then**
    Add $c[l]$ to $list$
  else
    $b \leftarrow$ the shortest path from lb to rb through $list$'s nodes;
    Add b to C'. Remove nodes in b from $list$ (except for lb, rb)
  end
end
Encode C' to an individual c';
return c'.

4.3 Population Selection, Termination Condition and Computational Complexity Analysis

Following the crossover and mutation operators, each individual $\mathbf{ind}$ is assigned a fitness value denoted as $f(\mathbf{ind})$ calculated using the objective function $\mathsf{N_m}$ as detailed in the previous section. The population is subsequently organized in ascending order based on the fitness values of individuals, then the top $\mathsf{Pop_{size}}$ individuals with the least fitness are selected to persist and evolve in the succeeding generations. The evolution process continues until the fixed number of generation $\mathsf{G}_{\max}$ is reached, which is the termination condition mentioned in line 3, Algorithm 1.

The computational complexity of computing the fitness function f for each individual is $\mathcal{O}(n)$. The computational complexity of crossover and mutation operators for each individual is also $\mathcal{O}(n)$. Hence, the computational complexity of KSB-EA is $\mathcal{O}(\mathsf{Pop_{size}}\mathsf{G}_{\max} n^2 (p_c + p_m))$.

5 Experiments

To prove the effectiveness of the proposed algorithm, we have conducted various experiments with different experimental scenarios to compare KSB-EA with prior algorithms in [22] and [8]. Thorough evaluations and analyses were performed to give deep sights into the experimental results. All experiments were conducted on a server with Intel core i5 v4@2.20 GHz, 16 GB RAM, and Windows 10 OS. The code was written in Java.

5.1 Experimental Settings

We considered two network scales, which are the small-scale one with a RoI of size 100[m] $\times$20[m], and the large-scale one with a RoI of size 500[m] $\times$100[m]. Based on the network scale, we set different values for parameters, as shown in Table 1. Here, $\mathcal{U}(a, b)$ denotes the uniform distribution over the interval $[a, b]$.

Table 1. Parameter settings for networks

Parameter	Small-scale networks	Large-scale networks
Number of static sensors n	$50, 80, 110, 140, 170, 200$	$1000, 1250, 1500, 1750, 2000$
Sensing radiuses r_1, r_2	$r_1 = 2, r_2 = 10$	$r_1 \sim \mathcal{U}[4, 6], r_2 \sim \mathcal{U}[10, 20]$
Half of sensing angle α	$60°$, $180°$	$\alpha \sim \mathcal{U}[30°, 90°]$
Sensor distribution	Uniform, Gauss, Exponential	
Number of barriers k	3, 4, 5, 6, 7	9, 11, 13, 15, 17
Desired probability $\mathcal{P}$	60%, 80%	60%, 80%
Physical properties	$\gamma_1 = \gamma_2 = 0.1$	$\gamma_1 = \gamma_2 = 0.1$

We defined an experimental instance as a combination of the **N**umber of **S**tatic sensors (NS), half of the sensing **A**ngle (A), the sensing **R**adius (R) and the sensor distribution (we use these abbreviations to name our experimental instances). We also named each experimental instance using the parameters. For example, in small-scale networks, NS200-A60-UNI describes an experimental instance with 200 static sensors, each sensor has half of the sensing angle of 60°C and sensor distribution is uniform. In large-scale networks, NS1000-GAU describes an experimental instance with 1000 static sensors and the sensor distribution is Gauss.

The number of barriers k, the desired probability $\mathcal{P}$, and the physical properties of sensors γ_1, γ_2 are not considered as parts of an experimental instance, since we run our experiments on the same experimental instance with different values of those. Facing direction β is the same for all experimental instances (always uniformly distributed in [0, 360]), thus not included in the experimental instance. Here, we called an input for the KSB-EA algorithm a data point, which combines an experimental instance and a specific value of $k, \mathcal{P}, \gamma_1, \gamma_2$. In total, we have 36 experimental instances of small-scale networks and 15 experimental instances of large-scale networks. In combination with different values of k and $\mathcal{P}$, we get 360 data points for small-scale networks and 150 data points for large-scale networks. Through various experiments, we have chosen the most suitable parameters for the proposed algorithm, which are population size $\mathsf{Pop}_{\mathsf{size}} = 2000$, the maximum number of generations $\mathsf{G}_{\max} = 500$, crossover rate $p_c = 0.5$ and mutation rate $p_m = 0.1$. Each data point was run 10 times and the average results are reported.

5.2 Experimental Results

In this part, we compare our proposed algorithm KSB-EA with the state-of-the-art algorithms which are AIPSO of [22] and KCES of [8]. AIPSO and KCES algorithms are replicated to compare with our proposed KSB-EA. The datasets of KSB-EA include datasets based on parameters from KCES in [8] and AIPSO in [22] to guarantee that comparisons between algorithms are fair. The parameters are chosen so that these algorithms share a number of fitness functions and calculations in common.

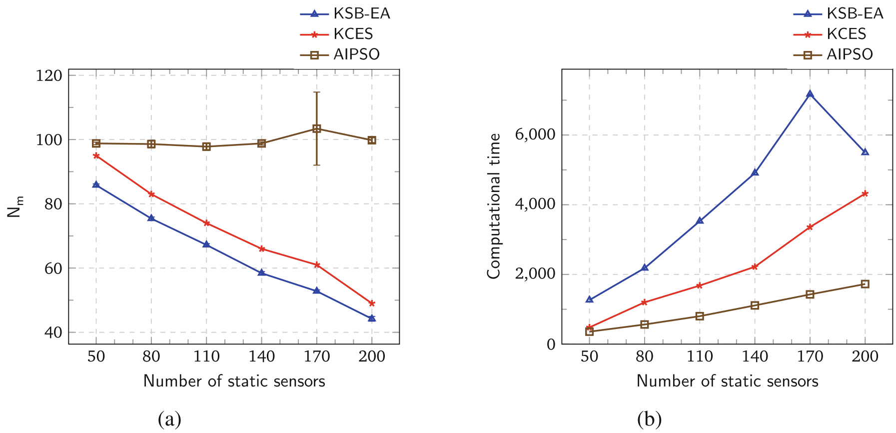
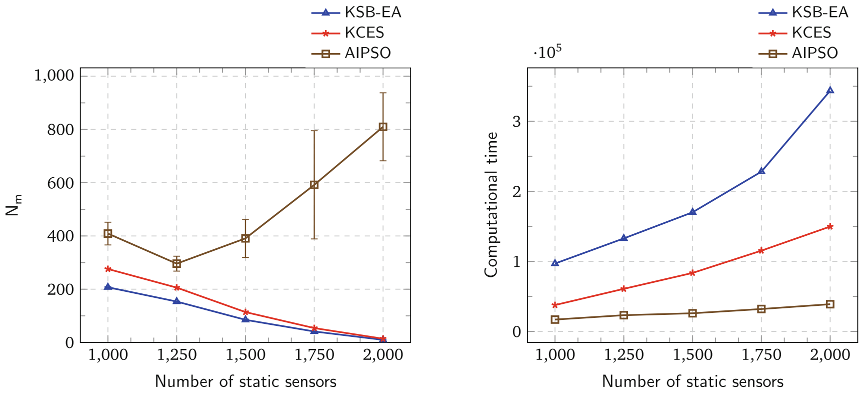


Fig. 5. Comparison between our proposed KSB-EA, KCES [8], and AIPSO [22] with different values of NS, fixed $k = 5, \alpha = 60$, uniform distribution (small-scale networks): (a) with respect to the number of required mobile sensors N_m; (b) with respect to computational time (ms).

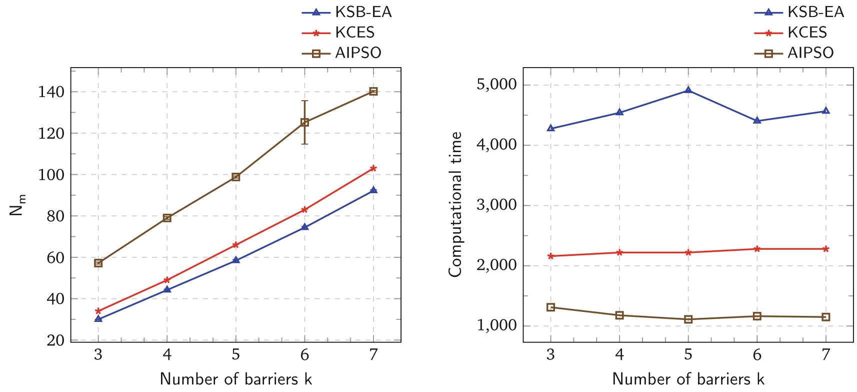
Figure 5a shows that KSB-EA obtains much better results than KCES and AIPSO with respect to the solution quality, i.e. the number of mobile sensors N_m. Especially, our KBS-EA is 40% better than AIPSO and 11% better than KCES on average respectively. The reason behind this is the effectiveness of different aspects of KSB-EA such as the individual representation, population initialization method, as well as our proposed evolutionary operators.

Figure 6 shows an even more significant difference between KSB-EA, KCES, and AIPSO. From Fig. 6a, we can see that N_m for AIPSO varies in the range [640, 880], while N_m for KSB-EA and KCES almost approach zero. Actually, on average, KSB-EA found the solution with $\overline{N_m} = 207.4$ for $n = 1000$ and $\overline{N_m} = 9.8$ for $n = 2000$ while KCES found the solution with $\overline{N_m} = 276.9$ for $n = 1000$ and $\overline{N_m} = 14.3$ for $n = 2000$. For standard deviation, it is obvious that AIPSO is highly unstable while KSB-EA and KCES give almost the same results for all runs. The computational time observed in Fig. 6b is not much different from that in Fig. 5b: in general, the computational time of KSB-EA is longer than that of AIPSO and KCES. This is reasonable because KSB-EA has more sophisticated operators than AIPSO and KCES, which is also a trade-off between the solution quality and computational time of the two algorithms.



(a) (b)

Fig. 6. Comparison between KSB-EA, KCES, and AIPSO with different values of NS, fixed $k = 13$, uniform distribution (large-scale network): (a) with respect to $\mathsf{N_m}$; (b) with respect to computational time (ms).



(a) (b)

Fig. 7. Comparison between KSB-EA, KCES, and AIPSO with different values of k, fixed $\mathsf{NS} = 140$, uniform distribution (small-scale network): (a) with respect to the number of required mobile sensors $\mathsf{N_m}$; (b) with respect to computational time (ms).

Comparison results between KSB-EA, KCES, and AIPSO when varying the number of barriers k are shown in Fig. 7. The results give the same insights as what we have analyzed so far, i.e. KSB-EA is much better than KCES and AIPSO with respect to $\mathsf{N_m}$ and standard deviation while the opposite holds for computational time.

6 Conclusion

The k-strong barrier coverage problem in heterogeneous multimedia sensor networks by minimizing the addition of mobile sensors called KSB-HeWMSN, which is the subject of investigation in this paper, has significant meaning for evaluating the quality of surveillance of wireless sensor networks. The KSB-HeWMSN problem is formulated as a combinatorial optimization problem, and then an elite evolutionary algorithm is proposed to solve it. To evaluate the performance of our algorithm, various experimental scenarios are designed, including small-scale and large-scale networks with different numbers and types of sensors, dimensions of ROIs, and deployment methods. The simulation results demonstrate the efficacy of the proposed algorithm in tackling the KSB-HeWMSN problem, surpassing the efficiency of previous algorithms.

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