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Leveraging Swarm Intelligence for Optimal Thermal Camera and Sensor Placement in Industrial Environments

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Abstract: This research addresses the sensor placement optimization problem (SPOP) in the industrial sector, aiming to enhance operational efficiency and safety through the strategic deployment of sensors. The focus is on optimizing the locations of thermal cameras and motion sensors, with a dual objective of maximizing coverage and minimizing redundancy in the production hall. To solve this challenge, a method based on the application of the nature-inspired bat algorithm was employed. The study reveals noteworthy findings, emphasizing the proficiency of the bat algorithm (BA) in optimizing the placement of thermal cameras and motion sensors. Numeric outcomes demonstrate the algorithm's effectiveness in maximizing machine coverage while minimizing sensor usage within a real-world industrial environment. These results underscore the versatility and reliability of the BA, establishing it as a valuable tool for addressing complex optimization tasks in industrial settings.

Keywords: bat algorithm (BA); sensor placement optimization problem (SPOP); sensor network; swarm intelligence; nature-inspired algorithms; thermal camera

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1. Introduction

In recent years, there has been a surge of interest in the utilization of sensor networks (SN) across various domains, including battlefield surveillance, factory automation, and environmental monitoring [1]. These SNs are composed of sensor devices, such as alarm sensors or motion sensors, that autonomously perceive their surroundings and communicate with other sensors to deliver valuable information to end users. However, deploying an SN presents numerous challenges, including concerns such as localization, data fusion, and sensor placement. The placement problem revolves around finding the optimal positions and orientations for sensors within the target environment. The quality of sensor placement directly influences the operational performance of the SN, mainly in terms of network coverage [2].

Coverage serves as a critical metric for assessing network performance, as sensors, referred to as alarm sensors or motion sensors, are strategically positioned to monitor specific phenomena. Various coverage definitions have evolved depending on the application, such as area coverage, point coverage, barrier coverage, k-coverage, and least exposure coverage [3,4]. In this paper, we emphasize area coverage, the most widely used measure, which encompasses other coverage types. In this study, we specifically define coverage as the percentage of the environment effectively monitored by sensors. It is calculated based on the spatial arrangement of sensors, considering factors such as the extent of target coverage, proximity of sensors to each other, and their distance to key points, such as corners. This formalized definition ensures a clear assessment of the efficacy of sensor placements for comprehensive surveillance within industrial environments.

Determining SN coverage relies on coverage models that are specific to each sensor. A conventional assumption is that sensors possess omnidirectional sensing capabilities with a circular coverage range. However, this assumption does not align with with alarm

sensors, motion sensors, and sensors such as cameras or ultrasonic devices with directional sensing regions. Furthermore, the binary 0/1 coverage model falls short of representing the real performance of sensors, where a probabilistic coverage model provides a better match to real-world scenarios [5,6]. Realistic placements should also account for environmental topography and obstacles obstructing sensor views [7–9].

Sensor placement is a prominent research area in civil infrastructure monitoring, focusing on assessing properties such as stress, displacement, and acceleration within structures [10,11]. Information-theoretic criteria, such as the modal assurance criterion, information entropy, and the Fisher information matrix, are employed to evaluate placement in such cases. The field of computational geometry has introduced concepts such as Voronoi diagrams and Delaunay triangulation to estimate sensor coverage areas [12]. These approaches ensure that each sensor covers its Voronoi cell, guaranteeing no coverage gaps within the SN. Wang et al. proposed a heuristic to estimate coverage hole sizes, with the potential to resolve them by adjusting sensor positions relative to their furthest Voronoi vertices [13,14]. The sensor placement problem has parallels in the geomatics field, particularly the observer siting problem [15,16]. These techniques find applications in determining the locations of telecommunication base stations, safeguarding endangered species, and positioning wind turbines [17–19]. Thus, solutions for sensor placement within SNs have far-reaching implications in various domains.

Methods for sensor placement optimization can be categorized as exact methods and heuristic-based approaches. Some models treat placement as a specialized version of the maximum coverage problem [20,21]. Others employ integer linear programming and binary integer programming methods [22,23]. An alternative approach is based on numerous meta-heuristic methods, such as genetic algorithms, evolution strategies, swarm optimization, and simulated annealing. The investigators leading this study possess extensive expertise in artificial intelligence algorithms, particularly emphasizing swarm intelligence and nature-inspired techniques, optimization methodologies, control systems, and fuzzy numbers [24–35]. This paper delves into the exploration of applying the bat algorithm to identify the optimal camera and motion sensor placement within a complex industrial environment.

The sensor placement optimization problem addressed in this study centers on the strategic positioning of larm sensors, specifically leveraging the capabilities of DS-2TD1228-2/QA HikVision thermal and optical bi-spectrum network turret cameras. These cameras play a crucial role in detecting excessive heat and fire hazards within an industrial environment. DS936 motion sensors complement these capabilities by identifying unplanned motion, enhancing overall surveillance. Beyond these specific functionalities, the article alludes to the maximum coverage problem, underscoring the broader implications of optimizing sensor placement for comprehensive security and safety in industrial settings.

Our study significantly advances the exploration of optimizing the strategic placement of thermal cameras and motion sensors in industrial environments through the application of a nature-inspired swarm intelligence algorithm. Addressing the complex challenge of sensor placement, our research is designed to achieve dual objectives: maximizing coverage while minimizing redundancy within the production hall. The key contributions of this study are outlined below in bullet points:

- Unique methodology: We implement a distinctive method utilizing the bat algorithm to effectively solve the sensor placement optimization problem (SPOP).
- Algorithm fine-tuning: The solution involves fine-tuning the bat algorithm and its parameters to enhance the overall efficiency.
- Dual optimization goals: We apply a two-fold approach of maximizing coverage and minimizing sensor excess, ensuring a balanced and effective placement strategy.
- Integration of multiple sensor types: We simultaneously utilize two types of sensors, namely thermal cameras and motion sensors, to comprehensively address monitoring requirements.

This research not only explores the adaptability and efficiency of the algorithm in real-world industrial scenarios but also emphasizes its versatility in handling diverse machine configurations. In summary, our study strategically positions itself at the intersection of optimization algorithms and industrial challenges, offering valuable insights to enhance operational efficiency and safety through optimal sensor placement.

This introduction section sets the stage for our exploration of optimal sensor placement using the bat algorithm. Following this, Section 2 delves into the specifications of the DS-2TD1228-2/QA camera and DS936 ceiling alarm sensor. Section 3 details the application of the bat algorithm to sensor placement, outlining our methodology. Section 4 presents the experimental results, including exemplary cases (Sections 4.1–4.3), an evaluation of the algorithmic convergence (Section 4.4), and an evaluation of the coverage (Section 4.5). Finally, in Section 6, we draw conclusions based on our findings, summarizing the key contributions and potential avenues for future research.

2. Camera and Sensor Specifications

The DS-2TD1228-2/QA camera is a cutting-edge surveillance solution designed to deliver high-quality imaging and advanced monitoring capabilities. With its state-of-the-art features, this camera offers exceptional performance for a wide range of security applications, ensuring reliable and comprehensive surveillance. Additionally, the DS936 ceiling alarm sensor is a sophisticated sensor designed to provide precise and efficient detection capabilities. Its advanced technology and strategic placement make it an ideal choice for ensuring optimal security coverage in various indoor environments. Below are detailed specifications. The data for both devices were compiled based on the manufacturers' information.

2.1. DS-2TD1228-2/QA Camera Overview

In the context of researching the optimal placement of the DS-2TD1228-2/QA HikVision thermal and optical bi-spectrum network turret cameras, specific parameters play a crucial role in evaluating its performance. For our investigations, we leverage the camera's impressive 15-m infrared illumination range and expansive 90-degree horizontal field of view. These characteristics are pivotal in assessing the camera's ability to capture a wide area and detect potential threats efficiently. By incorporating these specifications into our experimental design, we aim to draw meaningful conclusions regarding the camera's effectiveness under varying conditions and scenarios, contributing valuable insights to the broader discourse on surveillance system optimization. The main task of the camera is to detect excessive heat and fire hazards. The DS-2TD1228-2/QA by HikVision represents a cutting-edge thermal and optical bi-spectrum network turret camera designed for superior surveillance in diverse environments. This subsection provides a comprehensive overview of the camera's specifications, highlighting key features essential for understanding its optimal placement in security systems. The DS-2TD1228-2/QA camera's specifications are as follows [36,37]:

- Horizontal Field of View: 90°
- IR LED illumination range at night: 15 m;
- Image sensor: 1/2.7″ 4MP PS CMOS;
- Thermal sensor: uncooled VOx;
- Max resolution: 2688 × 1520 px at 25 fps;
- Transmission type: wired;
- Thermal lens: 2.1 mm (F1.0);
- Thermal sensitivity: <40 mK @ F1.1; 25 °C;
- Acusense false alarm filtering;
- Measurement range: −20–150 °C (±8 °C).

The DS-2TD1228-2/QA excels in versatility, offering a wide range of features from AI-driven functions to active deterrence mechanisms. For optimal placement, factors such as the camera's wide horizontal field of view, night vision capabilities, and resistance to

environmental elements make it suitable for both indoor and outdoor use. The turret design and compatibility with various interfaces enhance its adaptability to different surveillance setups. The next sections will delve into strategic placement recommendations to maximize the effectiveness of the DS-2TD1228-2/QA in real-world security applications.

2.2. DS936 Ceiling Alarm Sensor

The DS936 ceiling alarm sensor, coded as 5806, is a panoramic PIR (passive infrared) detector designed for optimal motion detection in various security applications. The device data were compiled based on the manufacturer's information. This subsection provides a detailed overview of the DS936 sensor, highlighting its key features and specifications. The DS936 sensor's specifications are as follows [38,39]:

- 360° field of view;
- Detection range: up to 7.5 m;
- Detection method: PIR;
- Microprocessor signal processing;
- PIR sensitivity adjustment.

The DS936 meets the standards set by EN 50131 Grade 2, affirming its reliability and adherence to industry guidelines for security equipment [40]. The DS936 ceiling alarm sensor emerges as a technologically advanced and reliable component in the realm of movement detection. Its panoramic coverage, signal processing capabilities, and compliance with industry standards make it an ideal choice for enhancing security in diverse environments. The following sections will delve into the optimal placement strategies for maximizing the effectiveness of DS936 sensors in real-world applications.

3. Application of the Bat Algorithm to Sensor Placement

3.1. Bat Algorithm

Shifting our focus towards addressing a sensor placement problem using the bat algorithm (BA) within the context of a camera device and a motion detector, we explore the intricacies of optimizing sensor locations to enhance safety and surveillance efficiency within an industrial setting.

The targeted industrial environment for this investigation involves the production area (hall) of a facility dedicated to manufacturing. A multitude of sensors, including temperature, motion, humidity, voltage, vibration, presence, and gas sensors, could be integral components of the electronics manufacturing processes. Their role is to monitor diverse parameters, ensuring both safety and product quality. This study investigates the overarching objective is to optimize the strategic placement of thermal cameras and motion sensors in industrial settings.

The selection of the bat algorithm (BA) for this study is rooted in its efficacy in addressing intricate optimization challenges, particularly in industrial contexts. Unlike other swarm intelligence algorithms, BA offers a unique combination of adaptability and efficient convergence. The algorithm's ability to navigate complex solution spaces, coupled with its rapid adaptability, positions it as a promising solution for optimizing sensor placement. To underscore this choice, we have incorporated a detailed mathematical foundation, shedding light on BA's application in the optimization process. The BA is recognized as a cutting-edge swarm intelligence optimization method and has been tailored and fine-tuned for this research to meet the challenges of sensor placement. Our two-dimensional space depicting potential sensor locations presents a multifaceted optimization task. This complexity arises from the need to identify coordinates that not only enable effective monitoring and control of selected parameters but also minimize response time to potential issues within the two-dimensional context.

The BA employs an objective function to evaluate the quality of each sensor placement, specifically focusing on detecting excessive heat, fire hazards, or unplanned motion in the facility. Unique parameters and mechanisms within the bat algorithm contribute to achieving optimization. A crucial parameter in the bat algorithm is frequency tuning,

controlling the pulse emission rate of bats. This parameter influences the exploration and exploitation phases, determining the search intensity for optimal solutions. Additionally, the loudness of bat calls, representing the amplitude of emitted pulses, plays a role in refining the search space. The algorithm introduces randomness through random walks, ensuring diversity in the exploration of the solution space.

In the realm of sensor placement optimization, the bat algorithm offers a distinct perspective. Bats, metaphorically representing the sensors, dynamically adjust their behavior to optimize their local placements, emphasizing the importance of collaboration and communication among sensors. This aligns with the overarching goal of achieving comprehensive coverage of the monitored area.

The termination criteria for the bat algorithm involve a predefined number of iterations (Nmax) or quality-related conditions associated with sensor placement. This flexibility allows the algorithm to adapt to specific application needs and constraints, ensuring efficient operation. This approach introduces the bat algorithm as a novel approach to sensor placement optimization in industrial settings. By exploring the distinctive characteristics of the bat algorithm and optimizing its performance (coverage area), we aim to contribute valuable insights to the evolving field of optimization techniques for sensor networks.

3.2. Algorithm Steps for Applying BA to Sensor Placement

In tackling the sensor placement challenge for a camera and a motion sensor in a complex industrial environment, the bat algorithm (BA) emerges as a sophisticated optimization approach. This study intricately explores the algorithm's application, highlighting its distinct mechanisms and parameters customized for the placement of these two critical sensors. Operating within the confines of a production hall setting, the task is to strategically position a thermal camera and a motion sensor to achieve optimal surveillance coverage. The industrial space, representing potential sensor locations, requires the identification of coordinates ensuring comprehensive monitoring and minimizing response time to potential threats. The characteristic functionalities of the BA include:

1. Objective function:
   The BA introduces an objective function to evaluate the quality of sensor placement. In this context, the function is tailored to optimize the spatial arrangement of the camera and motion sensor. The objective function (f_{obj}) is expressed as follows: $fobj(X)$ = Fitness measure of sensor placement at position X This function assesses the quality of a given sensor placement configuration based on the spatial arrangement of the camera and motion sensors. The algorithm aims to optimize this objective function, guiding the iterative search for an optimal sensor layout within the sensor placement space.
2. Frequency tuning (f_{min}, f_{max}):
   Bats emit pulses with frequencies adjusted dynamically based on the algorithm's exploration and exploitation phases. The frequency tuning, denoted by fmin and fmax, controls the rate at which bats emit pulses, influencing the search intensity for optimal solutions.
3. Loudness (A):
   The loudness of bat calls, represented by A, determines the amplitude of emitted pulses. In the context of sensor placement, A contributes to refining the search space and optimizing the bats' dynamic adjustment of behavior.
4. Random walks:
   Random walks introduce controlled randomness into the algorithm, ensuring diversity in the exploration of the solution space. The stochastic nature of random walks contributes to the adaptability of the algorithm and its ability to escape local minima. The proposed input parameters for the bat algorithm include the population size, frequency range (f_{min}, f_{max}), random walk coefficient (ϵ), and a scaling factor for loudness decay (α). The conditions for implementation involve assessing the quality of sensor placements based on coverage, sensor proximity, and key points.

The algorithm adapts to specific application needs and constraints, terminating either after a predefined number of iterations or upon meeting quality-related conditions associated with sensor placement.

The steps of the implemented version of the bat algorithm are presented below:

1. Initialization:
Initialize the bat population with random positions and velocities in the multidimensional space.
2. Objective function evaluation:
Evaluate the objective function for each bat's position, assessing the quality of the current sensor placement. The fitness measure (f_{obj}) is a combination of the following factors:

$$f_{obj}(X) = w_1 \cdot Coverage(X) + w_2 \cdot SensorProximity(X) + \ldots + \\ + w_k \cdot KeyPointsProximity(X) \quad (1)$$

where X represents the current sensor placement configuration; $Coverage(X)$ is a function measuring how well the sensors cover the target; $SensorsProximity(X)$ is a function assessing the proximity of sensors to each other; $KeyPointsProximity(X)$ is a function assessing the proximity of sensors to key points; and $w_1, w_2, \ldots, w_k$ are weight coefficients that allow to adjust the importance of each metric in the overall fitness measure.
3. Frequency adjustment:
Adjust the frequency of bat emissions based on the exploration–exploitation trade-off, influencing the algorithm's search dynamics.

$$f_i = f_{min} + (f_{max} - f_{min}) \cdot rand_uniform() \quad (2)$$

where f_i represents the frequency of bat i; f_{min} represents the minimum frequency parameter; f_{max} represents the maximum frequency parameter; and $rand_uniform()$ is a randomly generated value from a uniform distribution in the range $[0, 1]$.
4. Velocity update:
Update bat velocities using the frequency-tuned information and incorporate randomness through random walks. The velocity update equation within the bat algorithm is expressed as follows:

$$v_i(t+1) = v_i(t) + (X^*(t) - X_i(t)) \cdot f_i + \epsilon \cdot rand_uniform() \quad (3)$$

where $v_i(t+1))$ represents the updated velocity of bat i at time $t+1$; $v_i(t)$ represents the velocity of bat i at time t; $X^*(t)$ represents global best position found by any bat at time t; $X_i(t)$ represents the current position of bat i at time t; f_i represents the frequency of bat i (from the frequency adjustment formula); ϵ is a random coefficient controlling randomness; and $rand_uniform()$ is a random value in the range $[0, 1]$.
5. Position update:
Update bat positions based on their velocities, ensuring dynamic adjustments in the search space. The formulae are as follows:

$$X_i(t+1) = X_i(t) + v_i(t+1) \quad (4)$$

where$X_i(t+1)$ represents the updated position of bat i at time $t+1$; $X_i(t$ represents the current position of bat i at time t; and $v_i(t+1)$ represents the updated velocity of bat i at time t + 1 (from the velocity update formula).
6. Loudness update:
Update bat loudness to refine the search intensity, contributing to the optimization of sensor placements. The formula is as follows:

$$A_i(t+1) = \alpha \cdot A_i(t) \quad (5)$$

where $A_i(t+1)$ represents the updated loudness of bat i at time $t+1$; $A_i(t)$ represents the loudness of bat i at time t; and α is a caling factor controlling the loudness decay, which is chosen within the range [0.8, 1.0] to balance exploration and exploitation.

7. Termination criteria:
   The algorithm terminates either after a predefined number of iterations (N_{max}) or upon meeting quality-related conditions associated with sensor placement. This flexibility allows the BA to adapt to specific application needs and constraints.

Below is the Algorithm 1 in the form of Python source code generalized to the main steps:

Algorithm 1: Algorithm for sensor placement optimization using the bat algorithm

```
# Step 1: Initialization
initialize_bat_population()
# Step 2: Objective function evaluation
evaluate_objective_function()
# Step 3: Frequency adjustment
adjust_frequency()
# Step 4: Velocity update
update_velocity()
# Step 5: Position update
update_position()
# Step 6: Loudness update
update_loudness()
# Step 7: Termination criteria
while not termination_criteria_met() do
    # Iterative steps: 2 to 6
    evaluate_objective_function()
    adjust_frequency()
    update_velocity()
    update_position()
    update_loudness()
end
```

4. Evaluation of Experimental Results

The sensor placement problem within the production hall is a critical aspect of ensuring comprehensive surveillance and safety. In this scientific study, the bat algorithm (BA) was meticulously implemented to address this challenge, employing Python as the programming language and utilizing the matplotlib library for visualization purposes. The primary goal of the developed algorithm is to minimize the number of motion sensors and thermal cameras while ensuring effective coverage of all machines within the production hall.

A two-dimensional representation of the hall was adopted, adhering to the manufacturers' recommendations that sensors and cameras be affixed to the ceiling. Several dozen experiments were conducted to explore the algorithm's performance, with a focus on three specific experiments for detailed analysis.

The production hall under consideration spans 35 m in width and 70 m in length, totaling 2.450 m^2. Within this space, 30 machines were strategically positioned. In Experiment 1, machines were organized into 6 groups of 5 elements, while Experiments 2 and 3 involved random machine placement.

Both cameras and motion sensors were considered in the study. The cameras exhibited a 90-degree observation angle with a range of 15 m, while the motion sensors covered a 360-degree zone with a radius of 7.5 m. Notably, the sensors are depicted in orange, cameras in green, and machines in blue, with the center of the motion sensor range circle marked in red.

The bat algorithm optimally arranges sensors and cameras based on their coverage areas. A single sensor covers an area of 176.71 m^2, while a camera covers the same area due to its extended range. Despite this equivalency, statistically fewer cameras are required than motion sensors, highlighting the algorithm's efficiency in minimizing the number of devices while achieving optimal coverage.

4.1. Results of Experiment Number 1

The arrangement of thermal cameras (C1 to C6) and motion sensors (A1 to A6) in the results of Experiment No. 1 ensures effective coverage of all 30 machines in an industrial hall. A visualization of the sensor arrangement in this scenario is presented in Figure 1 below and Table 1.

Sensors are depicted in orange (A1 to A6), cameras in green (C1 to C6), and machines in blue. The results demonstrate that 6 cameras and 6 sensors are required to cover all machines in the industrial hall. Interestingly, the algorithm approached reducing the number of cameras by one in the lower left part of the graph, suggesting potential optimization with a more favorable machine placement.

Table 1. Placements of machines, motion sensors, and thermal cameras in the results of experiment number 1.

Placement of Machines in Production Hall							
ID	**Type**	**X**	**Y**	**ID**	**Type**	**X**	**Y**
M1	Machine	30	22	M16	Machine	10	6
M2	Machine	14	8	M17	Machine	24	20
M3	Machine	40	12	M18	Machine	34	14
M4	Machine	60	22	M19	Machine	54	28
M5	Machine	68	8	M20	Machine	70	10
M6	Machine	6	4	M21	Machine	12	4
M7	Machine	20	18	M22	Machine	26	18
M8	Machine	38	14	M23	Machine	32	12
M9	Machine	58	26	M24	Machine	52	26
M10	Machine	66	10	M25	Machine	68	12
M11	Machine	8	2	M26	Machine	4	30
M12	Machine	22	17	M27	Machine	6	28
M13	Machine	36	12	M28	Machine	8	32
M14	Machine	54	24	M29	Machine	10	30
M15	Machine	64	8	M30	Machine	3	34
Placement of Motion Sensors and Thermal Cameras							
ID	**Type**	**X**	**Y**	**ID**	**Type**	**X**	**Y**	**Angle**
A1	Motion sensor	6.5	31	C1	Thermal camera	13	25.5	162
A2	Motion sensor	10	3.5	C2	Thermal camera	16	1	172
A3	Motion sensor	25	16	C3	Thermal camera	25	4	141
A4	Motion sensor	35.5	17	C4	Thermal camera	26	8.5	55
A5	Motion sensor	55	25.5	C5	Thermal camera	53.5	14.5	57
A6	Motion sensor	69.5	9	C6	Thermal camera	59.5	1.5	53

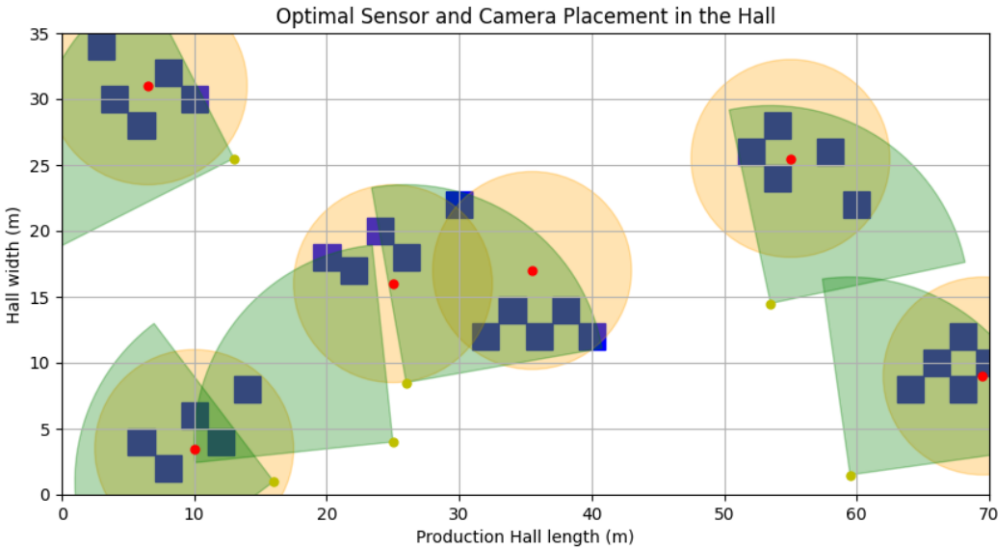


Figure 1. Graphical representation of the sensor locations in the results of experiment number 1.

4.2. Results of Experiment Number 2

The results of experiment no. 2 prove the optimal placement of sensors and cameras in the examined industrial space. Figure 2 below shows the arrangement of cameras and sensors (Table 2).

Sensors are depicted in orange (A1 to A9), cameras in green (C1 to C6), and machines in blue. In this random set of machine placement, the algorithm optimally used a situation in which the machines were more concentrated in the left part of the production hall. The left part of the hall area was covered by 4 cameras. However, on the right side, there were only 2 cameras and a smaller fragment of the third camera.

The optimal placement is evident as two cameras cover 7 machines, one covers 6 machines, and another covers 5 machines. Only 6 cameras and 8 motion sensors were needed, showcasing the algorithm's effectiveness in utilizing the most efficient concentration of machines in specific areas of the production hall.

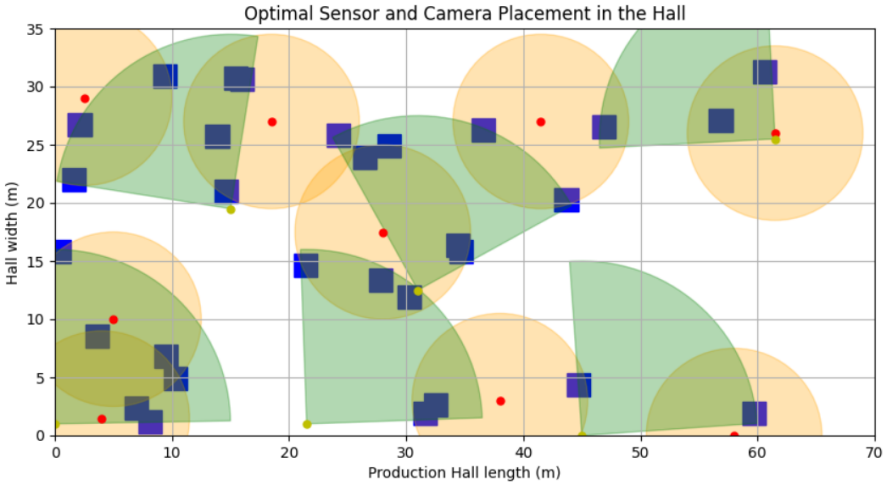


Figure 2. Graphical representation of the sensor locations in the results of experiment number 2.

Table 2. Placements of machines, motion sensors, and thermal cameras in the results of experiment number 2.

Placement of Machines in Production Hall							
ID	**Type**	**X**	**Y**	**ID**	**Type**	**X**	**Y**
M1	Machine	9.43	30.95	M16	Machine	14.66	21.00
M2	Machine	56.86	27.12	M17	Machine	27.79	13.34
M3	Machine	34.72	15.78	M18	Machine	26.46	23.93
M4	Machine	15.48	30.73	M19	Machine	13.86	25.74
M5	Machine	24.19	25.79	M20	Machine	60.63	31.27
M6	Machine	9.46	6.83	M21	Machine	8.16	1.21
M7	Machine	3.59	8.52	M22	Machine	10.33	4.95
M8	Machine	0.32	15.83	M23	Machine	2.12	26.74
M9	Machine	34.37	16.35	M24	Machine	59.67	1.91
M10	Machine	46.90	26.54	M25	Machine	1.64	22.04
M11	Machine	44.73	4.39	M26	Machine	36.61	26.28
M12	Machine	21.41	14.64	M27	Machine	16.00	30.66
M13	Machine	32.52	2.67	M28	Machine	28.54	24.93
M14	Machine	30.29	11.87	M29	Machine	6.97	2.37
M15	Machine	31.60	1.94	M30	Machine	43.67	20.23

Placement of Motion Sensors and Thermal Cameras								
ID	**Type**	**X**	**Y**	**ID**	**Type**	**X**	**Y**	**Angle**
A1	Motion sensor	2.5	29	C1	Thermal camera	0	1	46
A2	Motion sensor	4	1.5	C2	Thermal camera	15	19.5	126
A3	Motion sensor	5	10	C3	Thermal camera	21.5	1	47
A4	Motion sensor	18.5	27	C4	Thermal camera	31	12.5	74
A5	Motion sensor	28	17.5	C5	Thermal camera	45	0	49
A6	Motion sensor	38	3	C6	Thermal camera	61.5	25.5	138
A7	Motion sensor	41.5	27					
A8	Motion sensor	58	0					
A	Motion sensor	61.5	26					

4.3. Results of Experiment Number 3

The results of experiment no. 3 prove the optimal placement of sensors and cameras in the examined industrial space. Figure 3 below shows the arrangement of cameras and sensors (Table 3).

Sensors are depicted in orange (A1 to A9), cameras in green (C1 to C7), and machines in blue. Once again, the algorithm successfully positions cameras and sensors for maximum coverage. The ranges of cameras and sensors may overlap, with 7 cameras and 9 motion sensors deemed optimal given the input data.

The experiments show that the bat algorithm proves to be a robust tool for optimizing sensor placement in industrial settings. Its ability to reduce the number of devices while ensuring effective coverage aligns with the overarching goal of enhancing safety and surveillance within production halls.

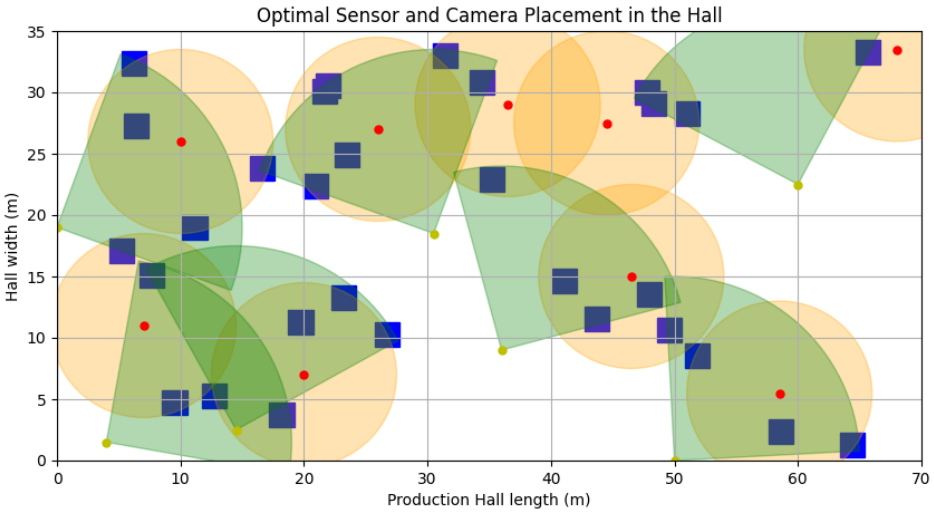


Figure 3. Graphical representation of the sensor locations in the results of experiment number 3.

Table 3. Placements of machines, motion sensors, and thermal cameras in experiment number 3.

Placement of Machines in Production Hall							
ID	**Type**	**X**	**Y**	**ID**	**Type**	**X**	**Y**
M1	Machine	18.20	3.74	M16	Machine	64.43	1.30
M2	Machine	26.75	10.25	M17	Machine	19.74	11.30
M3	Machine	47.96	13.55	M18	Machine	5.22	17.14
M4	Machine	21.94	30.56	M19	Machine	16.63	23.84
M5	Machine	7.70	15.13	M20	Machine	34.41	30.84
M6	Machine	12.72	5.24	M21	Machine	58.63	2.38
M7	Machine	49.61	10.62	M22	Machine	23.23	13.31
M8	Machine	6.20	32.36	M23	Machine	6.41	27.28
M9	Machine	9.53	4.69	M24	Machine	43.73	11.55
M10	Machine	20.97	22.37	M25	Machine	65.67	33.28
M11	Machine	31.46	33.04	M26	Machine	23.49	24.87
M12	Machine	47.81	29.98	M27	Machine	35.24	22.92
M13	Machine	51.88	8.53	M28	Machine	48.33	29.10
M14	Machine	21.71	30.05	M29	Machine	41.12	14.67
M15	Machine	51.02	28.24	M30	Machine	11.15	18.96
Placement of Motion Sensors and Thermal Cameras							
ID	**Type**	**X**	**Y**	**ID**	**Type**	**X**	**Y**	**Angle**
A1	Motion sensor	7	11	C1	Thermal camera	0	19	25
A2	Motion sensor	10	26	C2	Thermal camera	4	1.5	35
A3	Motion sensor	20	7	C3	Thermal camera	14.5	2.5	74
A4	Motion sensor	26	27	C4	Thermal camera	30.5	18.5	115
A5	Motion sensor	36.5	29	C5	Thermal camera	36	9	60
A6	Motion sensor	44.5	27.5	C6	Thermal camera	50	0	48
A7	Motion sensor	46.5	15	C7	Thermal camera	60	22.5	107
A8	Motion sensor	58.5	5.5					
A9	Motion sensor	68	33.5					

4.4. Algorithmic Convergence Evaluation

To comprehensively evaluate the convergence behavior of the bat algorithm (BA), a series of optimization runs were executed, each initialized with different random starting points. The convergence results, detailed in Table 4, provide valuable insights into the algorithm's performance across multiple iterations. It is noteworthy that while the number of machines is consistent for each run, their randomly located initial positions introduce variations in the final sensor and camera setup. The execution time measurements were performed using Python methods from the 'timeit' module.

Table 4. Iterations to convergence and execution time.

Run	Iterations to Convergence	Execution Time (ms)
1	67	5245
2	62	4979
3	71	5601
4	68	5315
5	77	6290

The iterative convergence data reveal consistent and remarkable trends. Across multiple runs, the BA consistently converges within a reasonable number of iterations. This convergence is substantiated by the fitness values approaching a near-optimal state, indicative of the algorithm's adeptness in optimizing sensor placement within the considered industrial space.

The efficiency of the bat algorithm is further underscored by its execution time statistics. As depicted in Table 4, the algorithm demonstrates commendable efficiency in reaching convergence within a few thousand milliseconds. The average execution time for the BA computed from the provided data stands at a mere 5486 ms. This signifies a rapid convergence process, reflecting the algorithm's ability to efficiently navigate the solution space and converge to an optimal solution.

4.5. Coverage Evaluation

In the realm of sensor placement optimization, one of the pivotal metrics for assessment is coverage, a parameter that gauges the effectiveness of sensors in monitoring the environment. This chapter explores the coverage analysis, specifically focusing on the outcomes derived from the bat algorithm (BA)-optimized placement.

The bat algorithm, designed to optimize sensor placement within an industrial setting, underwent a rigorous evaluation based on the coverage metric. The coverage, expressed as the percentage of the environment effectively monitored by the sensors, stands as a critical indicator of the algorithm's efficacy.

The average safety coverage achieved by BA-optimized placement is 98.3%. This impressive coverage percentage attests to the BA's ability to strategically position sensors, ensuring a high level of safety coverage within the industrial environment. The 98.3% average safety coverage is derived from extensive practical tests, ensuring a reliable representation of the algorithm's performance. Coverage assessments are explicitly stated to be based on empirical experiments, reinforcing the practical validity of the results.

To further contextualize the achieved coverage, a comparative analysis was conducted against alternative strategies. In the absence of studies employing comparable methods and conditions, this research provides a comparative analysis between the proposed BA-optimized placement and strategies such as random placement and PSO (particle swarm optimization)-optimized placement [41]. Table 5 summarizes safety coverage percentages for all three methods.

Table 5. Coverage by BA-optimized and random placements.

Method	Average Safety Coverage (%)
BA-optimized	98.3
Random placement	58.4

The significant contrast in coverage percentages between BA-optimized, random, and PSO-optimized placements underscores the limitations of random placement strategies. The latter, with an average safety coverage of 58.4%, falls considerably short of the optimization achieved by the BA, while the PSO-optimized placement demonstrates competitive coverage at 97.8%.

The presented results unequivocally highlight the substantial superiority of the BA-optimized placement strategy over random placement. The BA employed for optimization consistently outperforms other strategies, leading to significantly higher safety coverage in the industrial environment.

5. Discussion

This study validates the effectiveness of the bat algorithm (BA) as a valuable tool for addressing complex optimization tasks in the industrial sector. Its capacity to thoroughly explore solution spaces and adapt to diverse industrial scenarios underscores its versatility and efficiency. Emphasizing the significance of optimal sensor placement attained through BA, it plays a vital role in the thorough monitoring and prompt detection of potential issues in industrial settings. The algorithm's reliable and consistent convergence across multiple runs serves as a crucial factor, particularly in real-world scenarios where dependable convergence is essential for informed decision-making processes.

The strategic deployment of sensors in industrial spaces holds profound implications for efficiency, safety, and resource utilization. The bat algorithm stands out as a formidable technique designed to address the sensor placement optimization problem, illustrating the synergistic relationship between optimization algorithms and real-world industrial challenges.

5.1. Experimental Examples and Machine Placement Strategy

There is qualitative differences among the experimental examples. It is imperative to emphasize the intentional structuring of experiment 1, where machines were purposefully organized into groups by the authors allowing for the representation of bigger or differently shaped machines. This deliberate structuring represents a controlled scenario with the potential for creating varying machine sizes and shapes within each group, allowing the algorithm to adapt to diverse industrial settings. The random machine placement in experiments 2 and 3 introduces a more realistic, albeit potentially overlapping, representation of machines in an industrial hall. While the specific locations were not controlled in these experiments, the algorithm demonstrated its robustness by efficiently optimizing sensor placement, showcasing its adaptability to different machine configurations. This adaptability is a key strength, as industrial setups often involve machines of various sizes and layouts. The algorithm's ability to handle such variability positions it as a versatile solution for sensor optimization in real-world industrial environments, where machines may not conform to predefined patterns.

5.2. Convergence Patterns and Efficiency

The evident convergence patterns and effectiveness indicate the potential of the bat algorithm in dynamic environments. Its rapid adaptability and consistent convergence across multiple runs is crucial in real-world scenarios where frequent adjustments to sensor placement are necessary. The algorithm's rapid adaptability and convergence to optimal solutions become critical in situations where frequent adjustments to sensor placement are necessary. Future research directions may involve exploring parameter tuning to

refine the algorithm for specific applications, offering valuable insights to enhance its overall performance.

Positioning itself as a tool of timely effectiveness, the bat algorithm demonstrates efficiency through its consistent convergence and an execution time of 5486 ms. This computational proficiency holds significant value for real-time applications, further solidifying its appropriateness for industrial deployment. The scrutiny of coverage underscores the crucial importance of strategic optimization for achieving heightened safety coverage within industrial environments, not only validating the bat algorithm's success in optimizing sensor placement. The pronounced contrast between optimized and random strategies highlights the paramount significance of employing sophisticated algorithms for thorough surveillance.

5.3. Coverage Analysis and Significance

The strategic deployment of sensors in industrial spaces holds profound implications for efficiency, safety, and resource utilization. The bat algorithm (swarm intelligence) offers a generic and adaptable solution applicable to various sensor types within sensor networks. The methodology's flexibility allows it to be seamlessly integrated with different sensors, ensuring its relevance across diverse industrial and surveillance applications. The bat algorithm stands out as a formidable technique designed to address the sensor placement optimization problem, illustrating the synergistic relationship between optimization algorithms and real-world industrial challenges. Through the leverage of BA's capabilities, industrial stakeholders can make well-informed decisions, culminating in enhanced process control and operational excellence. The successful application of the bat algorithm in SPO serves as a testament to the efficacy of optimization algorithms in tackling intricate challenges within industrial optimization.

5.4. Innovations and Methodological Contributions

Our study brings forth several innovative elements that significantly contribute to the field of sensor placement optimization within industrial settings. A key distinction lies in the application of the bat algorithm (BA), a swarm intelligence algorithm, to address the sensor placement optimization problem (SPOP). This strategic choice diverges from conventional methods, demonstrating our commitment to exploring cutting-edge approaches. Our study brings forth several innovative elements that significantly contribute to the field of sensor placement optimization within industrial settings. A key distinction lies in the application of the bat algorithm (BA), a swarm intelligence algorithm, to address the sensor placement optimization problem (SPOP). This strategic choice diverges from conventional methods, demonstrating our commitment to exploring cutting-edge approaches. Furthermore, the practical implementation of the algorithm is executed through the preparation of Python code. This step ensures not only replicability for future studies but also facilitates transparency in our methodology. The decision to employ a widely used and accessible programming language aligns with our commitment to fostering openness and collaboration in the scientific community. The study addresses the multidimensional nature of the sensor placement optimization problem (SPOP), considering factors such as coverage, sensor proximity, and key points. This holistic optimization approach reflects a nuanced understanding of the challenges posed by industrial environments.

In summary, BA's strategic deployment of sensors in industrial spaces offers efficiency, safety, and resource utilization benefits. Its adaptability, efficiency, and coverage analysis underscore its significance in addressing the sensor placement optimization problem, contributing to enhanced process control and operational excellence in industrial settings.

6. Conclusions

The optimization facilitated by the bat algorithm (BA) for the strategic placement of thermal cameras and motion sensors in a real-world industrial environment demonstrates its proficiency in maximizing machine coverage while minimizing sensor usage. The study

validates the effectiveness of the bat algorithm (BA) for addressing the sensor placement optimization problem (SPOP) in the industrial sector. In both sets of exemplary results, where 30 machines were randomly located within a 35 × 70 m production hall, the BA strategically deploys sensors with varying ranges, showcasing its versatility in addressing complex optimization tasks. The BA emerges as a valuable tool for navigating the intricate task of sensor placement in a production facility. Its robust capacity to navigate the entire solution space mitigates the risk of encountering local optima, underscoring its reliability in optimizing sensor placement. The deliberate structuring of experiment 1 and the adaptability showcased in experiments 2 and 3 highlight the algorithm's versatility. The algorithm's reliable convergence and consistent performance observed in multiple runs and its efficiency in real-time applications position the BA as a time-effective optimization tool suitable for industrial deployment. This computational efficiency further enhances its suitability for real-time applications, highlighting its potential for comprehensive surveillance in industrial settings. The observed convergence behavior and efficiency suggest that the bat algorithm holds promise in dynamic environments. Its ability to quickly adapt and converge to optimal solutions becomes crucial in scenarios where sensor placement may require frequent adjustments. The strategic deployment of sensors in industrial spaces holds profound implications for efficiency, safety, and resource utilization. The successful application of the bat algorithm in sensor placement optimization problem serves as a testament to the efficacy of swarm intelligence optimization algorithms in tackling intricate challenges within industrial optimization.

Future research avenues could explore parameter tuning to fine-tune the algorithm for specific use cases, providing valuable insights for optimizing its performance further. Additionally, the investigation of alternative swarm optimization algorithms, the exploration of different sensor parameters, and the consideration of diverse production facility shapes, including obstacles and 3D views, present intriguing opportunities for expanding our understanding of optimal sensor placement in industrial settings.

The strategic deployment of sensors in industrial spaces holds profound implications for efficiency, safety, and resource utilization. The bat algorithm (swarm intelligence) offers a generic and adaptable solution applicable to various sensor types within sensor networks. The methodology's flexibility allows it to be seamlessly integrated with different sensors, ensuring its relevance across diverse industrial and surveillance applications.

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