An Intelligent Spatial Military Intrusion Detection using Reactive Mobility Unmanned Vehicles Based on IoT and metaheuristic Optimization Algorithm

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Abstract

One of the most significant uses of the Internet of Things is military infiltration detection (IoT). Autonomous drones play a major role in IoT-based vulnerability scanning (UVs). By relocating UVs remotely, this work introduces a new algorithm called the Moth-Flame Optimization Algorithm (MFO). In particular, MFO is used to proactively manage UVs under various scenarios and under different intrusion-covering situations. According to actual studies, the suggested algorithm is both profitable and efficient.

Keywords: Internet of Things (IoT); Spatial coverage; Intrusion Detection; Moth-Flame Optimization; Metaheuristic.

1. Introduction

The usages of the Internet of Things (IoT) recently invade our modern life via its various applications in smart cities [1-3], smart health [4], smart traffic [5-7], and smart petroleum system [8], etc. One of the most significant applications in military surveillance. IoT is used extensively in many vital applications, such as monitoring force protection areas and detecting enemies' movements [9]. Usually, these military sensors are set up on Unmanned Vehicles (UVs) which remotely take orders (See Figure 1). In particular, the movement reactions are controlled by an embedded Artificial Intelligence (AI) technique. Nature-inspired metaheuristic algorithms can be considered one of the most effective AI techniques for solving IoT-based allocation problems. Generally, metaheuristics are AI-based algorithms that are often used in solving optimization problems with a reasonable cost and near-optimal quality. The operation of metaheuristics mainly depends on the efficient blending of exploration and exploitation phases [10]. The first phase indicates the investigation of unvisited search areas. On the other hand, the latter means searching for the best solution found so far.

When it comes to UV management, heuristic methods are primarily responsible for determining the appropriate spatial patterns of UVs to optimize the visibility of monitoring sensors. This issue can be solved using metaheuristics in a variety of different ways. What an issue has been addressed by Particle Swarm Optimization (PSO) by Ismail and Manaf [11]. Another Voronoi-based PSO algorithm was

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developed by Ab Aziz et al. [12] to reduce the proportion of uncovered regions in the observed area. [13] proposes a Voronoi-inspired Pso technique with an extra restriction for energy saving by introducing fuzzy penalty variables concerning the features great of every sensor. The Voronoi-based PSO method was enhanced in [14] by adding an extra phase that kept sensor beginning locations, IDs, and the permanent product in a repository. As a result, the sensors were allocated to the ultimate result, which optimizes the miles driven while minimizing the amount of time it takes. Xia [15] presented a hybrid binary representation of PSO. PSO and the Artificial Fish Swarm Algorithm (AFSA) [16] were used together to pick the most cost-effective sensors. Shuffled Frog Lunging Algorithm (SFLA) [18] and PSO (Sun and Zhao [17]) were used to solve the issue. PSO was used to cover Digital Elevation Models (DEMs) in a 2.5-dimensional region in [19]. The authors of [21] presented PSO for sensor reallocation based on a virtual force approach. An algorithm called GA was employed by Yildirim et al. [22] to optimize the area and the specified goal while ensuring that sensors were connected. In [23], the authors used the Ant Colony Optimization (ACO) method to tackle the sweep coverage issue. As few mobile devices as possible were used to keep data transmission to a minimum, however, this did not compromise data quality. For the measurement of perceived optimization issues, Hajjej et al. [25] suggested a binary version of the Flower Pollination Algorithm (FPA). In order to maximize penetration whilst minimizing energy usage and connection, [26] put a cross-version of FPA onto the market. [27] suggested a grid-based, the number of co Krill herd methods to handle the range optimization issue.

An inhabitant's meta-heuristic method, the moth-flame optimization algorithm mimics the nighttime activity of moths around a flame. MFO follows a set of generic stages that are almost identical to that of other meta-heuristic algorithms.

I. Moths (i.e., matrix M) are generated at random as a starting population.
II. A random set of beginning flames is generated (i.e. matrix F);
III. Are using a fitness calculator to determine the productivity of moths
IV. Moths flying over the flame in a spiral formation
V. Increasing the number of embers in the fire;
VI. Step 3: If the terminating condition is not met, go back to step 3 and try again;
VII. Restoring the moth to its natural habitat is a possible remedy.

The MFO algorithm is explained in the following paragraphs. The MFO algorithm relies heavily on moths and fires. During the evening, the moth flies in a straight line around the fire. As soon as the butterflies see a source of light, they immediately begin to fly directly toward it. The moth circles the source of light in a spiral motion if it approaches it.

Furthermore, a first effort is made to study and verify the effectiveness of the moth-flame optimization technique in the suggested approach. It has been shown that moth-flame optimization algorithms perform better than other meta-heuristics used to solve optimum equipment production scheduling issues in sustainable fuel systems when contrasted to the most popular meta-heuristics currently in use.
As aforementioned, the MFOA is used in the proposed optimum sizing technique to solve the optimization problem subject to the planning and decision-making level limitations. For optimum scaling studies of

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sustainable power systems, MFOA's result is evaluated against the most often used optimization algorithm on the basis, such as PSO and GA, as well as a long-established state-of-the-art optimizer, such as the hybrid GA-PSO approach. Comparing the accuracy of the solutions and the number of iterations needed to reach convergence is two important criteria. As in the case of the MFOA, the PSO, the GA, and the combination GA-PSO are integrated into the suggested optimum sizing technique to optimize the system. These values are used to establish the mutation and crossover probability in the GA and the hybrid GA-PSO, respectively; the perceptual factor, socialization element, and flywheel mass in the PSO and the hybrid GA-PSO, respectively. Furthermore, the population numbers and the maximum number of generations for all four algorithms are considered to be 45 and 300, respectively, in order to create a fair comparison.

Mirjalili came up with the idea for the MFO heuristic algorithm, which takes inspiration from nature (2015). Observing how moths navigate at night, we may deduce that they constantly aim to keep a stable inclination to the light and to make a circular scrolling route. The exchange of position vectors enables moths to fly in one, several, or even hyperdimensional dimensions. The moth's spatial location is treated as a variable in these dimensions, and a collection of all possible spatial locations might be an MFO answer.

That said, fires or insects are both viable options and only vary in their update/treatment methods. During the search, moths fly across the search space in many different spatial locations, but flames are the ideal spatial position for moths, thus they mark them to prevent losing their best answer. Moths constantly share their knowledge and inform each other about the best spots they've found.

Mirjalili (2015) describes three multi-objective optimization problems (steps) in MFO that are based on optimization techniques, which (i) include the inhabitants of moths and their strength and conditioning, (ii) the lookup space and how moths move around it (exchanging experiences and updating positions), and (iii) checking whether or not the halt criterion is comfortable. MFO is a global optimization technique (step).

Using the Moth-Flame Optimization Algorithm (MFO), the UVs in the unmanned vehicles may be reallocated to cover the identified target in diverse settings and conditions. As for the remaining sections, they are as follows: the issue description is in part 2, followed by the observation area partition technique in section 3, the MFO is addressed in section 4, the findings and discussion are in section 5, then the conclusion and recommendation for future are in section 6.

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Figure 1: Unmanned Vehicles [28, 29].

2. Problem Formulation

[30] defines the range optimization issue as two-dimensional sensor nodes of n sensors, each of which is linked to the other through a two-way communication link (ROI). x_i y_i and z_i are the spatial coordinates of each sensor $(i = 1, \ldots, n)$ and their respective sensing zones (i=1,...,n). In addition, all sensors do have the following features: The energy is the same throughout all sensor detecting ranges. The normal distribution applies to all sensor sensing ranges. Thus, the border effect is abandoned since it is less than the ROI length. Double the size of the sensing zone is required for the surveillance zone. The sensors are all homogenous and separate from one another.

The following lemmas are provided for determining the extent of each sensor's coverage:

If the Euclidean distance among q and s i is less than or equal to z_i, then s i is regarded to cover q.

A is regarded to be covered by s_i when the Euclidean distance among both points q in A and s is less than z_i.

Specifically, the ROI effective penetration is measured in terms of the network coverage ratio. Because of this, the level of coverage provided by a network has a substantial impact on its overall quality. It's possible to calculate the percentage of coverage using this formula.

$$p_{cov} = \frac{area\left(\left(\cup_{i=1,\ldots n} s_i\right) \cap \overline{\overline{ROI}}\right)}{\overline{\overline{ROI}}} \quad (1)$$

p_{cov} is the cell service rate, $(\overline{\overline{ROI}})$ is the entire area of ROI and _$\cup_{i=1,\ldots n} s_i$ is the total of any and all encompassed sub-areas by every s_i sensor.

This issue is all about finding an optimal percentage of coverage that maximizes the overall coverage, based on prior lemmas:

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$$max \quad \frac{CA}{\overline{ROI}}\ \% \qquad (2)$$

where CA is the total covered area.

In this paper, the proposed algorithm is used for giving reallocation orders to UVs with surveillance sensors. In particular, additional constraints are added to ensure the coverage of the targets while preserving the coverage percentage.

3. Grid Quorum Based Strategy

ROI has virtually divided into orthogonal grid cells in the Grid consensus-driven placement technique. The variety of sensors in every cell is taken into account while calculating the solution's efficiency. In those other terms, grid unanimity may be used to calculate ROI covering as [12]:

$$C_{IR} = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} c_{ij}^{s}}{m \times n} \qquad (3)$$

A sensor s covers C_{IR}, which is the cells of a grid in the nth row of the grids, and c_{ij}^{s} is the overall cell coverage rate.

4. Moth-Flame Optimization Algorithm (MFO)

Mirjalili [33] proposed the MFO as a nature-inspired meta-heuristic algorithm. MFO was inspired by the nighttime flight patterns of moths. Furthermore, they use transverse orientation, a flying technique wherein the moths fly at a predetermined angle relative to the moon, as seen in Figure 2. When it comes to moths, any light source, such as a candle or the sun, is considered a moon. Molecules fly in a circular pattern near light sources. Initial population production and storing of fitness data form the basis of the method. In the next stages, the best ideas that moths (flames) have come up with thus far are saved and modified as necessary. A logarithmic spiral solution is used to develop the new answer for each iteration. On the premise that the moth is the starting point of the spirals and the flame is the endpoint, the movement is a logarithmic spiral. The departure of the spiral can't go beyond the search region. "

This formula is used to determine the new moth's position:

$$x_{ij}{}^{new} = |F_{ij} - x_{ij}|.\, e^{b\beta}.\cos(2\pi\beta) + F_{ij} \qquad (4)$$

In this example, the potential solution $x_{ij}{}^{new}$ represents the newly created solution, whereas F_{ij} represents the flame solution, x_{ij} is the current method, and b is a preset constant (equal to one). (As seen in Figure 3.)

The adaptive method used by MFO to update the solution is another source of strength. In other words, F t is swapped out with a different flame solution that is adaptively generated using an adaptive number, as seen below: F_t

$$m = round(N - t * \frac{N-1}{T}) \qquad (5)$$

A maximum of N iterations, with each iteration consisting of t iterations, equals a total of T iterations. Every answer to the suggested MFO issue reflects the location of a UV point in the sky UV (x,y)

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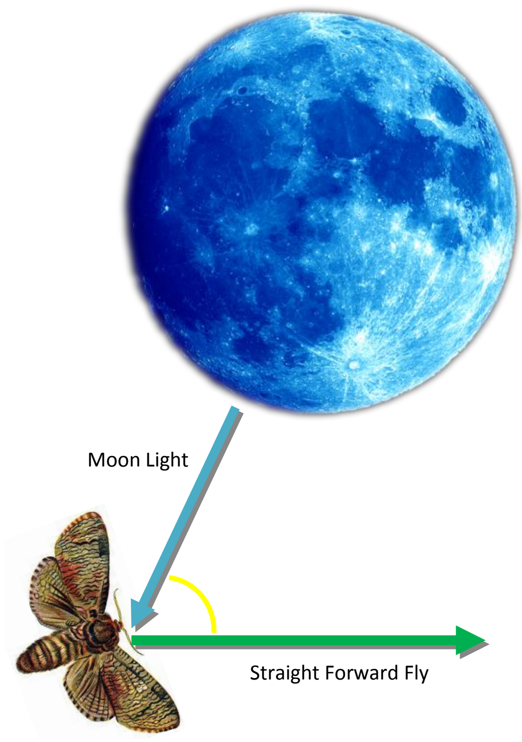

Figure 2: Moth Flying Mechanism.

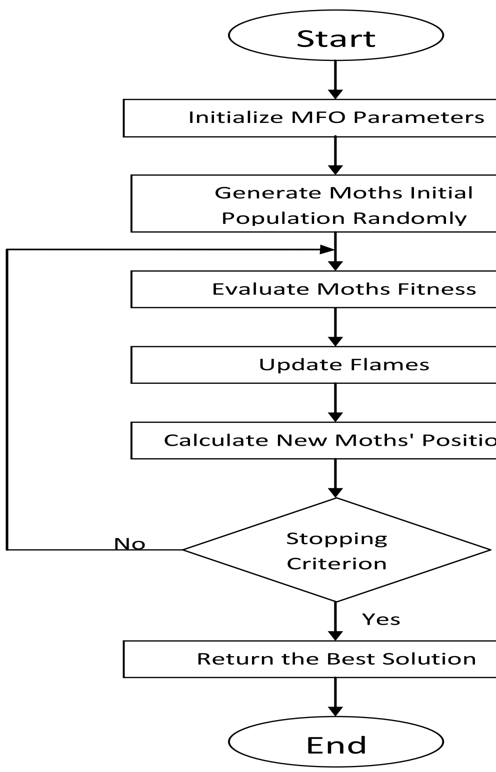

Figure 3: MFO Flowchart.

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5. Experimental Results

In this section, MFO is compared with PSO and Harris Hawks Optimizer (HHO) [34]. Mathematica 2015 is used to write all the algorithms. The maximum convergence rate and the number of candidate solutions are both set to 100 for all methods. Other algorithmic settings are left unchanged. Each algorithm is performed 30 times to ensure that the findings are statistically sound. Space incursion detection situations are shown in Table 1. A computer operating platform with a 2.60 GHz CPU and 6 GB of RAM is used for the modeling of the scenarios. Figures 4, 5, and 6 depict MFO's stimulation of area and incursion coverage. To maintain the needed condition of incursion cover whilst increasing the covering percent, this method proposes moving unmanned drones around as indicated. Table 2 summarises the study's findings in terms of descriptive statistics. Using MFO, the optimal solutions may be found without breaking any constraints. MFO, for instance, uses a predetermined number of UVs to shield the incursion. When it comes to PSO and HHO, this goal can't be reached after 30 runs because of the coverage incursion limitation, which is particularly problematic for the third instance.

Table1: Scenarios of Intrusion Spatial Detection

Military Scenarios	**Area**	**No. of Sensors**	**Radius**	**No. of Intrusions**	**Each intrusion must be covered by**
Scenario1	10 X 10	3	3	1	2 UVs
Scenario2	50 X 50	4	10	3	1 UV
Scenario3	100 X 100	35	20	5	4 UVs

Table2: Descriptive Statistics of MFO & Comparators.

		Minimum	Maximum	Mean	Std. Deviation
Scenario1	MFO	**59.4104**	70.5215	**69.598874**	**2.0126654**
	PSO	N/A	72.7891	N/A	N/A
	HHO	N/A	69.8413	N/A	N/A
Scenario2	MFO	**42.9450**	**48.9043**	**48.189158**	**1.5157903**
	PSO	N/A	45.8285	N/A	N/A
	HHO	N/A	48.7889	N/A	N/A
Scenario3	MFO	**99.9231**	100.0000	**99.997437**	**.0140388**
	PSO	N/A	N/A	N/A	N/A
	HHO	N/A	100.0000	N/A	N/A

N/A means Not A number.

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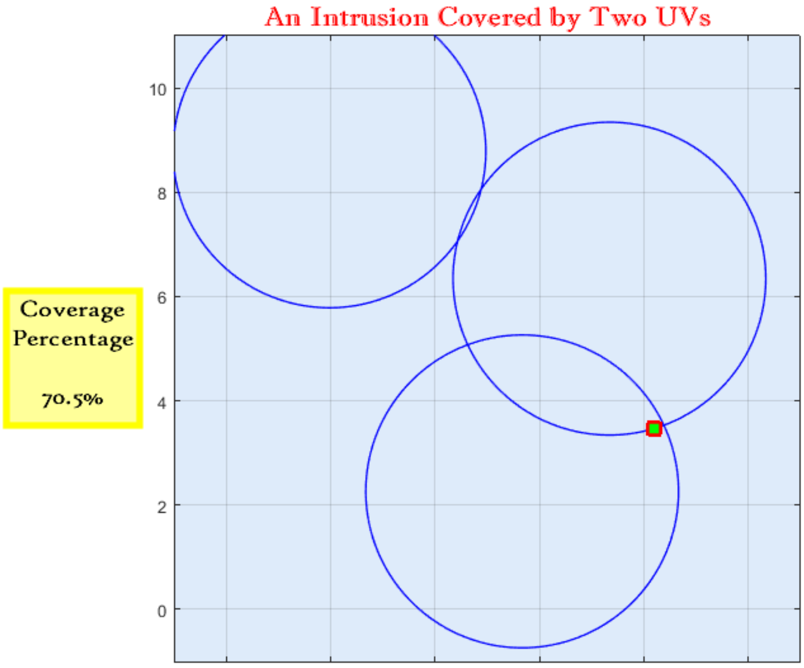

Figure 4: MFO Coverage Simulation of Scenario1.

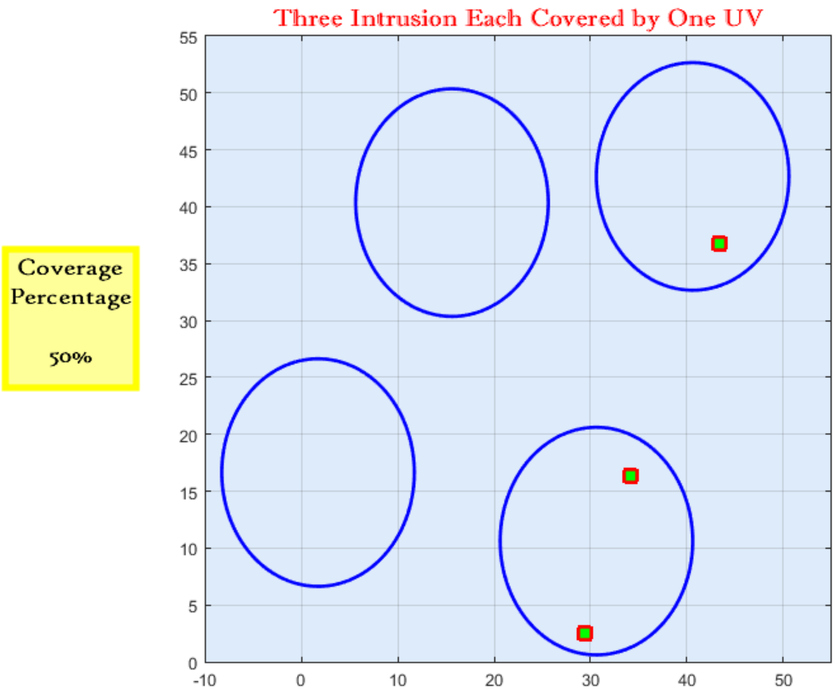

Figure 5: MFO Coverage Simulation of Scenario2.

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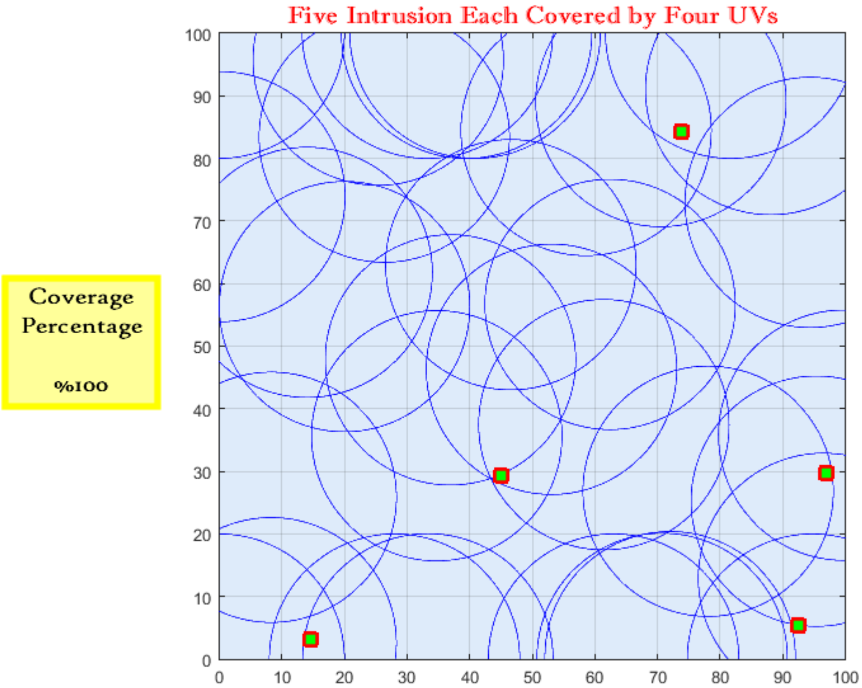

Figure 6: MFO Coverage Simulation of Scenario3.

6. Conclusion

In military IoT apps, connectivity is a major concern. For military intrusion detection, MFO is employed in this article, but with extra limits on the number of sensors that can cover them. In order to accommodate all kinds of surveillance sensors, the grid-based area subdivision is used. Various metaheuristic algorithms are compared to MFO. The experiment results indicate that the suggested method is more efficient and consistent than other algorithms. The simulation shows the MFO's capabilities and speed for real-time vehicle allocation.

The suggested technique may be improved by making use of Fuzzy Logic (FL) to calculate the parameters of the MFO. Aside from emergency service, sensor deployments, and cyberdefense, MFO may be used to solve additional military optimization algorithms.

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