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PTZ-Surveillance coverage based on artificial intelligence for smart cities

Khalid A. Eldrandaly[a], Mohamed Abdel-Basset[b,*], Laila Abdel-Fatah[b]

[a] Department of Information Systems, Faculty of Computers and Informatics, Zagazig University, Zagazig, Sharqiyah, 44519, Egypt
[b] Department of Decision Support, Faculty of Computers and Informatics, Zagazig University, Zagazig, Sharqiyah, 44519, Egypt

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ABSTRACT

Surveillance cameras have a plethora of usages in newly born cities including smart traffic, healthcare, monitoring, and meeting security needs. One of the most famous new cites is the Egypt's new administration capital “New Cairo”. The new administration capital of Egypt mainly characterizes with the green life style via the "Green River ". In this paper, a new enhanced Artificial Intelligence (AI) algorithm is introduced for adjusting the orientation of Pan–Tilt–Zoom (PTZ) surveillance cameras in new Cairo. In other words, the new proposed algorithm is used for improving the field of view (FOV) coverage of PTZ cameras network. For validating the proposed algorithm, it is tested on many scenarios with different criterions. After that, the proposed algorithm is applied to adjust the PTZ monitoring cameras in the green river which locates on new administrative capital as an equivalent to the river Nile. In addition, it compared with several other AI algorithms through the appropriate statistical analysis. The overall experimental results indicate the prosperity of the proposed algorithm for increasing the coverage of the PTZ surveillance system.

1. Introduction

The wave of technological development has swept through our world until most of the modern residential cities have become smart cities characterized by automation and intelligence. The smart city can be defined as a high-level ontology that describes the semantic categories including a series of innovations in urban systems sustained by broadband networks, sensors, data management technologies, software applications and e-services (Komninos & Mora, 2018). Roughly speaking, the smartness of the city is determined by the Structure and Functions of its Semiotics (Data, Information, Knowledge) management system. So, these functions can be summarized as (Ramaprasad, Sánchez-Ortiz, & Syn, 2017):

$$Functions \subset [Sense, \ Monitor, \ Process, \ Translate, \ Comunicate] \quad (1)$$

Therefore, one of the most important pillars of such a smart urban is the surveillance systems so-called image sensors/camera networks, which can be considered vision organs of the smart city.

Network cameras are used in smart cities across the globe for monitoring, surveillance and other security needs. Due to the Internet of Things (IoT) comes to life; they extend well beyond simple surveillance tasks to other application scenarios. There are several types of cameras which differ in servo capabilities, sensor element, lens type, etc. In general, they can be categorized into three main types (Erdem & Sclaroff, 2006): Fixed Perspective, Omni-directional, and Pan-Tilt-Zoom (PTZ) cameras. The former has a fixed position, orientation, and focal length. The second has a full 2π horizontal coverage but it has a small focal length which may cause undesirable lens aberration effects. The last type of cameras (PTZ) is adjustable in a predefined range. They can be rotated horizontally and vertically around their (Tilt) and (Pan) axis respectively. Also, some PTZ cameras have an adjustable focal length (Zoom).

The cameras network become an essential component of a city cloud computing center for a variety of its services ranging from safety and security to green environmental solutions. These cameras are not in direct communication with the main cloud center but are controlled by and work through what called Fog computing. Fog computing (Eldrandaly, Abdel-Basset, & Shawky, 2019; Sodhro, Luo, Sangaiah, & Baik, 2019) is the practice of real-time data processing near the edge of the network, where the data is generated, instead of processing data in a centralized warehouse. Thus, cameras network take their instruction and adjustment from this edge computing. In addition, fog computing supports the employment of artificial intelligence for enhancing the performance of cameras systems (See Fig. 1).

In this paper, a new improved AI algorithm called "Enhanced FireFly Algorithm (EFA)" is proposed. EFPA is used to enhance the coverage of PTZ cameras network by altering the orientation of them. Many experiments on different scenarios are made and the overall results

* Corresponding author.
E-mail addresses: khalid-eldrandaly@zu.edu.eg (K.A. Eldrandaly), analyst_mohamed@yahoo.com (M. Abdel-Basset), lilaabdelfatah@zu.edu.eg (L. Abdel-Fatah).

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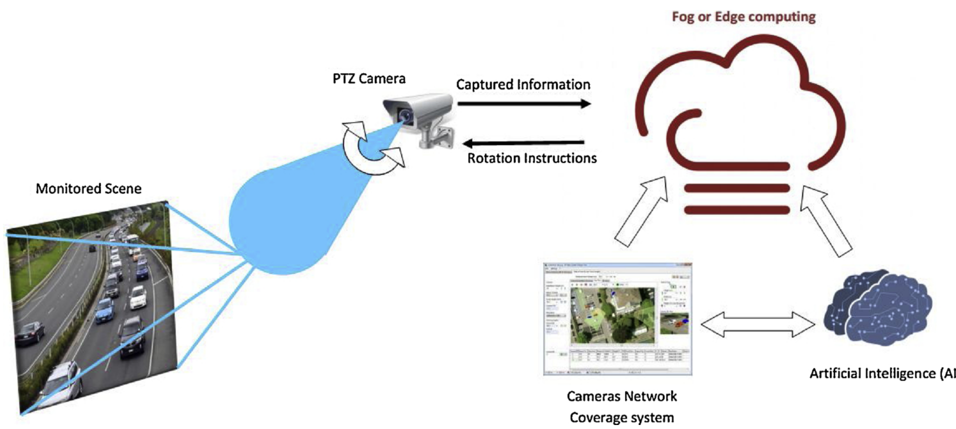

Fig. 1. Fog Adjustment of PTZ cameras.

indicated the efficiency of the proposed algorithm. The present paper has many exclusive contributions, as follows:

- An Enhanced FA (EFA) is proposed for solving area coverage problem of cameras network.
- For the first time in literatures, the new administrative capital of Egypt is highlighted.
- An optimization-based surveillance system is introduced for the constructed part of the Green River in Egypt.

The remaining paper structure is as go behinds: Section 2 represents a literature survey, the problem is defined in Section 3, the methodology is showed in Sections 4, 5 depicts the results of the proposed algorithm, the application of EFA on the Green River is represented in Section 6. Finally, in Section 7, the conclusions and future works are given.

2. Literature review

Several researches have been proposed from time to time in order to enhance the citizen's life in smart cities. For instance, the authors (Hashem et al., 2016) introduced a comprehensive study of the rule of Big Data (BD) (Oussous, Benjelloun, Lahcen, & Belfkih, 2018) in smart cities. In addition, the authors proposed a reference business model of big data for smart cities. In (Koo, Yoo, Lee, & Zanker, 2016; Yuan, Xu, Qian, & Li, 2016), the authors handling the technology of smart tourism management systems by proposing frameworks that illustrated the smart interaction between travel data and tourists. The authors in (Park, Lee, Yoo, & Nam, 2016) studied the effect of Facebook© technologies on the smart tourism ecosystem in Korea. Also, Arenas et al. (Arenas, Goh, & Urueña, 2019) studied the impact of Information Technology (IT) on the smart tourism ecosystem in Spain. Nyberg (Nyberg, 2018) suggested the reorganization of the energy sector (Smart Grid (SG) (Zafar et al., 2018)) in Japan. The author argued that the energy sector reorganization required broad tailoring of information for keeping users to develop an active relationship with infrastructure. Rana et al. (Rana et al., 2018) made a field study in Indian to identify the development barriers of smart cities. In addition, the authors validate the field study results with sensitivity analysis. The authors also have prioritized the development barriers based on employed fuzzy Analytic Hierarchy Process (AHP) technique (Chan, Kumar, Tiwari, Lau, & Choy, 2008). The barriers with descending priority are Governance, Economic, Technology, Social, Environmental, and Legal and Ethical. Also, the authors in (Ismagilova, Hughes, Dwivedi, & Raman, 2019; Obaidat & Nicopolitidis, 2016; Osman, 2019; Rawat & Ghafoor, 2019) proposed valuable study for enhancing the operability of smart cities. Regarding the power consumption, Gellert et al. (Gellert, Florea, Fiore, Palmieri, & Zanetti, 2019) proposed a methodology for forecasting the electricity production and consumption in buildings of smart cities.

Ultimately, smart cities seek for the amelioration of city smartness through the employment of systems and applications based on AI. One of the main effective contributions of AI is the computation of solutions for highly complex problems with multiple requirements and objectives (Martins, 2018). For instance, Kane et al. (Kane et al., 2015) introduced a nature-inspired smart city architecture that simulates the human nervous system called Reflex-Tree. As real human nervous, the proposed architecture is able to process and respond to huge data streams through automated “reflex” circuits in the sensing and distributed computing architecture. Reflex-Tree was successfully applied to two case studies: city power supply network and gas pipeline management. In (Cosido, Loucera, & Iglesias, 2013), the authors introduced a model for finding cycle route in Santander. The proposed model dealing with the resultant problem using soft computing, Geographic Information System (GIS), and AI algorithms (metaheuristics). Horng (Horng, 2015) proposed a two-phases parking system for smart parking. The proposed system can offer rapid parking service via the adoption of AI-based cellular automata mechanism and cognitive radio network model. In (Li, Shahidehpour, Bahramirad, & Khodaei, 2017), the authors introduced a two-level model for determining adaptive traffic signal time settings. The first level minimizes the average travel time via the determination of the traffic signal settings. The second level tries to reach the network equilibrium via the employment of an AI optimization algorithm. Rahbari et al. (Rahbari et al., 2018) proposed an AI-based model for managing Smart Grid (SG) that connecting electric vehicles. The proposed model was able to reach high convergence and robustness via the usage of AI optimization algorithm and neuro-fuzzy inference system. In (Islam, Razzaque, Hassan, Ismail, & Song, 2017), the authors presented a real-time processing model of healthcare big data in smart city. The proposed model used an AI algorithm for scheduling Virtual Machines (VMs) that efficiently handling the heterogeneous incoming healthcare data. For more information about the usage of nature-inspired algorithms in smart cities, see (Duan, Edwards, & Dwivedi, 2019; Zedadra et al., 2019).

As discussed above, AI plays an important role in managing and facilitating life in smart cities. One of the AI techniques is metaheuristics. Metaheuristics are AI heuristics that able to find an optimal /near-optimal solution for complex optimization problems with a reasonable time (Glover, 1986). The efficiency reason behind the prosperity of metaheuristics is a good mixture of exploration and exploitation (Blum & Roli, 2003). The exploration is the investigation of the new abandoned search region. Whereas, the exploitation aims to search around the founded best solution. Roughly speaking, metaheuristics simulate natural phenomenon or behaviors of creatures. For instance, Genetic Algorithm (GA) (Sampson, 1976) emulates Darwin’s principle "Survival of the fittest" through the biological evolution

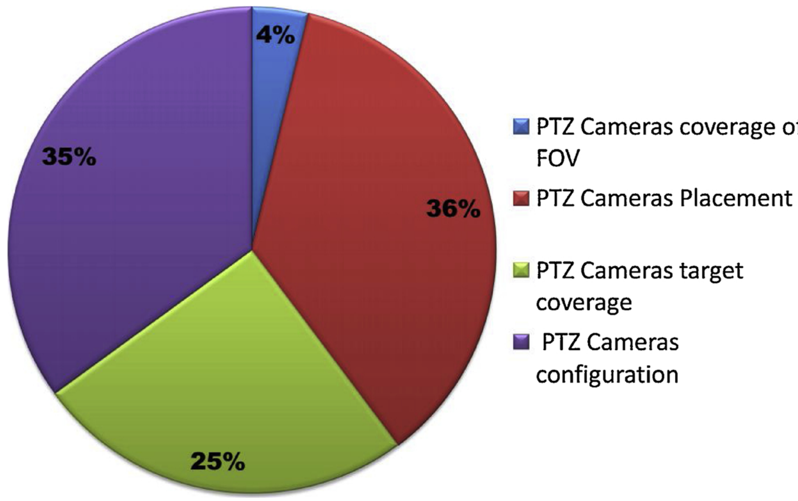

Fig. 2. Literatures of PTZ Cameras Optimization Problems (forecast).

process of chromosomes. Particle Swarm Optimization (PSO) (Eberhart & Kennedy, 1995) was inspired by the behavior of animals in society as flocking birds. Flower Pollination Algorithm (FPA) (Yang, 2012) simulates the flowers reproduction process. Salp Swarm Algorithm (SSA) (Mirjalili et al., 2017) was inspired by the behaviour of salps when navigating and foraging in oceans.

In a few recent years, the prosperity of metaheuristics glows in smart city applications. In particular, surveillance and monitoring applications in smart cities can be enhanced and optimized by metaheuristics. To be precise, cameras networks (especially video cameras) are very expensive sensors not only in financial costs but also in bandwidth. Thus, the optimization problem of camera network coverage needs to be optimized by metaheuristics (Murray, Kim, Davis, Machiraju, & Parent, 2007). Xu (Xu, Lei, & Hendriks, 2011) applied PSO for solving the problem of camera network coverage. After several experiments, the proposed algorithm proved that it can be applied to the design of any practical camera network. In (Jiang, Wang, Chen, Zheng, & Yao, 2012; Peng & WeiDong, 2013), kinetics based Particle Swarm Optimization (PSO) approach was proposed. In the proposed method, each camera is repelled by both other cameras and obstacles by combining a kinetics constraint factor with PSO. Wang et al. (Wang, Gu, Zhang, & Chen, 2019) proposed a new improved version of PSO that aiming to find the best placement of cameras. In addition, the recharging of cameras is taking into account via the usage of Fuzzy c-means clustering algorithm for determining the charging stations.

As shown, the literatures handling Field Of View (FOV) coverage of PTZ cameras network are almost scarce. In other words, as shown in Fig. 2, these literatures are relatively rare while the other PTZ cameras' optimization problems represent the majority of related PTZ cameras' optimization problems. In this paper, a new enhanced metaheuristic algorithm is introduced for solving such a problem aiming to reach better practical coverage.

3. Problem definition

The camera network ROI coverage optimization can be defined as using fewest possible cameras to monitor/inspect a fixed area or maximizing the ROI coverage of a network with a fixed number of cameras. The coverage problem can be divided into three subcategories: point coverage, barrier coverage, and area coverage (Cardei & Wu, 2004; Gage, 1993; Ramsden, 2009). The point coverage problem, the objective is to cover a set of target points. The barrier coverage aims to correctly identify intruders that cross a barrier. The area coverage is the most studied coverage problem where the main dual objectives are maximizing the probability of area coverage while minimizing the uncovered regions in this area (holes).

3.1. Cameras network area coverage problem

Suppose that cameras network is deployed for monitoring a Region Of Interest (ROI). Each camera c_i has a sensing sector that consists of a range r, a Field Of View (FOV) which shaped as fan area with angle φ, and orientation vector $\vec{d_i}$ (See Fig. 3(a)). For any two points U and V,

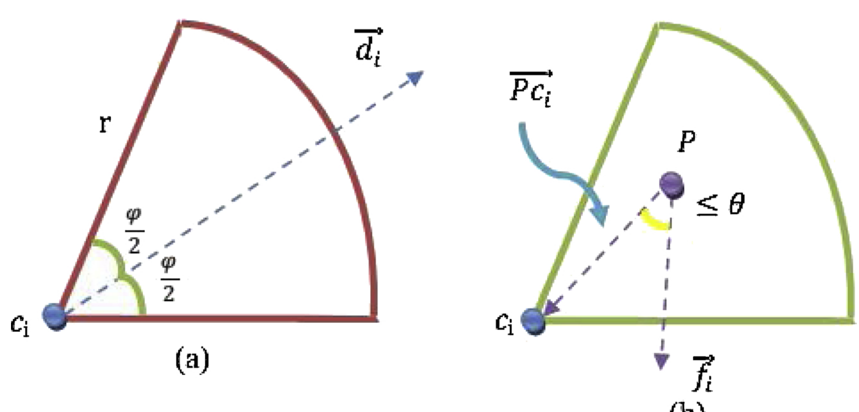

Fig. 3. Camera Coverage Model.

the term $\|UV\|$ means the Euclidean distance between them. For any two vectors $\vec{v_1}$ and $\vec{v_2}$, the term $\alpha(\vec{v_1}, \vec{v_2})$ represents the angle between them that ranging from zero to π. Consequently, a point P is covered by a camera c_i if the following conditions are realized (Wang & Cao, 2013):

$$\|Pc_i\| \le r \tag{2}$$

$$\alpha(\vec{d_i}, \vec{c_iP}) \le \frac{\varphi}{2} \tag{3}$$

From the previous, the following lemmas can be expressed:

Lemma 1. *The problem of cameras network coverage can be defined as a point P id full covered if for any facing direction $\vec{f_i}$ there is a camera c_i such that a point P is covered by a camera c_i. Also, the angle between $\vec{f_i}$ and $\vec{Pc_i}$ is lower than the effective angle, as* (He, Shin, Zhang, Chen, & Sun, 2016):

(4)$\alpha(\vec{f_i}, \vec{Pc_i}) \le \theta$

$$\alpha(\vec{f_i}, \vec{Pc_i}) \le \theta \tag{4}$$

where θ is a predefined parameter between $[0, \frac{\pi}{2})$ (See Fig. 3(b)).

Lemma 2. *Suppose a network of N cameras with the same r and φ. All cameras are distributed randomly over ROI. The expected coverage (EC) can be calculated as* (Erdem & Sclaroff, 2004):

(5)$EC = 1 - \left(1 - \frac{\varphi r^2}{\mathrm{A(ROI)}}\right)^N$

$$EC = 1 - \left(1 - \frac{\varphi r^2}{\mathrm{A(ROI)}}\right)^N \tag{5}$$

where $\mathrm{A(ROI)}$ denotes the area of ROI and N is the total number of cameras.

4. Methodology

4.1. Firefly Algorithm (FA)

Firefly Algorithm (FA) (Yang, 2008, 2009) was inspired by the behaviour of flashing fireflies. i.e. FA focuses on the firefly observation of light at its position when trying to move to a greater light-source than its own. Besides, the following rules should be considered:

1) For all fireflies, their sex is neglected.
2) Firefly attracts to another firefly that is brighter than it.
3) The solution fitness is determined by the firefly brightness.

```
Firefly Algorithm
initialize fireflies population
formulate light intensity I associated with objective function
define light absorption coefficient γ
while(termination criterion doesn't met )
for each firefly i
 for each firefly j
if Ij < Ii
move firefly i towards firefly j
end if
update attractiveness β
evaluate new solutions and I
end for j
end for i
rank fireflies
end while
Update the current best position x*
end
return x*
```

Fig. 4. FA Pseudo-code.

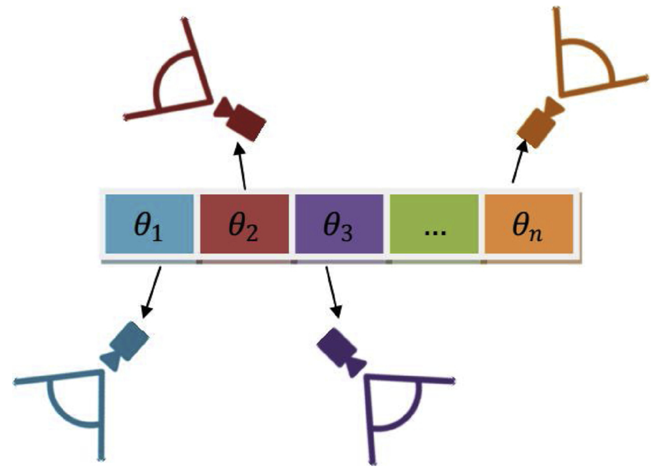

Fig. 5. Fireflies Encoding.

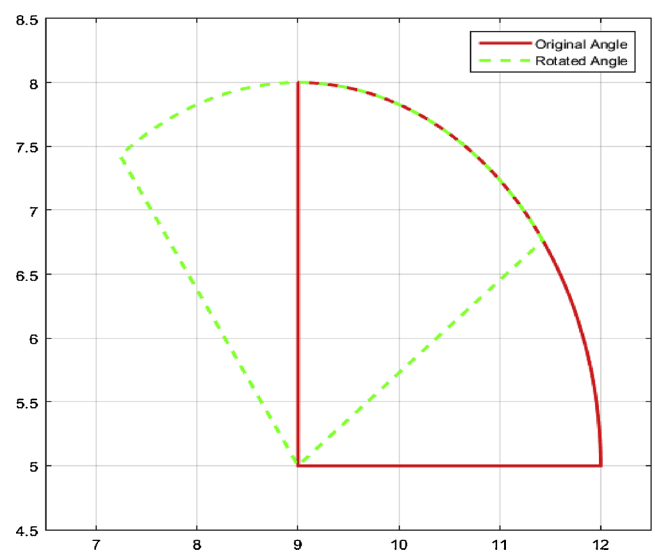

Fig. 6. Effective Angle Rotation.

The formulation of FA is based on a physical formula of light intensity I which is inversely proportional to the square of a particular distance r from the light source as:

$$I = \frac{I_0}{r^2} \tag{6}$$

where I_0 is the light intensity at distance zero. By taking the light intensity reduction via the air absorption coefficient, the light intensity I varies with the square of the distance r as:

$$I = I_0 e^{-\gamma r^2} \tag{7}$$

Thus, the attractiveness β of a firefly can be computed as:

$$\beta = \beta_0 e^{-\gamma r^2} \tag{8}$$

where β_0 is the attractiveness at the distance $r = 0$.

The movement of a firefly i to another brighter firefly j can be calculated as:

$$x_{i+1} = x_i + I_0 e^{-\gamma r^2} \varepsilon_1 (x_j - x_i) + \alpha \varepsilon_2 \tag{9}$$

where ε_1 is a random number between [0,1] drawn from the uniform distribution. While ε_2 is a random number drawn from Gaussian distribution and α is a controlling parameter.

The FA search procedure begins by generating random fireflies. During the search iterations, all candidate solutions are evaluated based

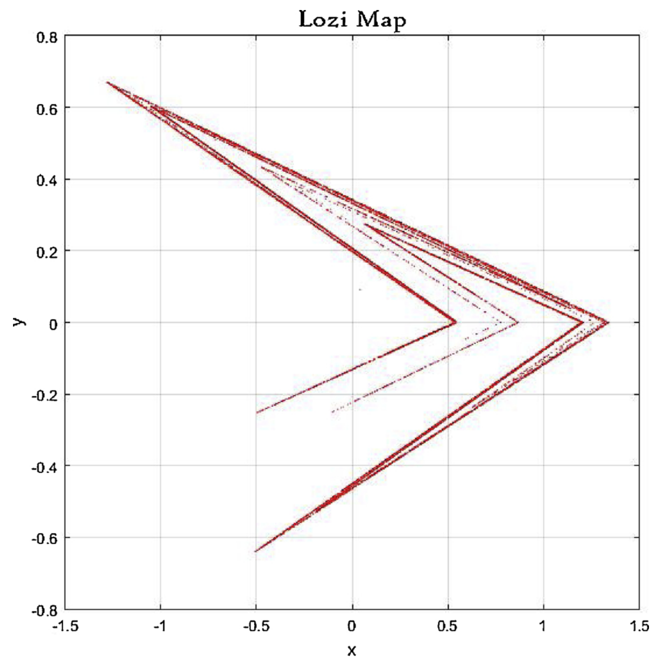

Fig. 7. Lozi chaotic map.

on the objective function. Then the light intensity of each candidate solution is updated according to its fitness value. After that, they are sorted according to their light intensity. After that, fireflies begin to update their positions attracting to the brightest firefly (see Fig. 4).

4.2. Fireflies encoding for camera coverage problem

In order to formulate the fitness function of coverage problems, several methods were proposed including grid-based, Voronoi-based, and virtual force-based. The grid-based methods (Shen, Chen, & Sun, 2006) divide the interest region into cells then sum the covered cells to the total number of grid cells. In the Voronoi-based algorithms (Arslan, Min, & Koditschek, 2018), a set of static sensors is selected then the area is divided by a Voronoi diagram. Then, another set of mobile sensors move to minimize the number of holes. In this method, the holes are determined with the distance from Voronoi edges and vertices. The virtual force-based algorithms (Zou & Chakrabarty, 2003) assume that sensors have potential fields that exert virtual forces. Hence, they repel each other until there is no overlapping between them. Thus, it is a waste of energy.

In order to deploy FA for adjusting PTZ cameras, fireflies should be encoded as camera's effective angle θ in a two dimensional *ROI*. For instance, let n be the total number of PTZ cameras. Then, the Fireflies encoding will be as shown in Fig. 5. Note that, the location of each camera is assumed to be fixed. In addition, *ROI* is virtually split into isometric grid cells, and the number of cells that covered by cameras is considered for computing the solution fitness. The best solution is the PTZ cameras orientations that maximize the coverage percentage which can be calculated as:

EFA Algorithm

initialize fireflies population
formulate light intensity I associated with objective function
define light absorption coefficient γ
while(termination criterion doesn't met)
for each firefly i
for each firefly j
if $I_i < I_j$
if $rand < 0.9$
move firefly i towards firefly j
else
if $rand \geq 0.5$
move firefly i towards search space lower bound with Lozi map
else
move firefly i towards search space upper bound with Lozi map
end if
end if
end if
update attractiveness β
evaluate new solutions and I
end for j
end for i
rank fireflies
Update the current best position x^*
end while
return x^*

Fig. 8. EFA Pseudo-code.

Table 1
Experiment dataset characteristics.

Datasets	IR Area	NO. of Sensors	Radius	Expected coverage
Dataset 1	10 × 10	6	3	35.59%
Dataset 2	25 × 25	10	5	27.32%
Dataset 3	50 × 50	25	10	54.98%
Dataset 4	150 × 150	50	25	66.81%

Table 2
The compared algorithms parameters values.

Algorithm	Parameters	Value
EFA	Light Absorption Coefficient	1
	Attraction Coefficient Base Value	2
	Border attraction probability	0.1
DE	Lower Bound of Scaling Factor	0.2
	Upper Bound of Scaling Factor	0.8
	Crossover Probability	0.2
SSA	Switching Probability	0.5
PSO	Acceleration coefficients c_1, c_2	2
	Inertia Weight Factor	0.729
WOA	Switching Probability	0.5

Table 3
Descriptive statistics of EFA and the comparators.

Datasets	Algorithms	Worst	Best	Mean	Standard Deviation
Dataset 1	EFA	51.24%	72.72%	61.87%	5.85E+00
	PSO	42.14%	71.07%	55.95%	6.92E+00
	SSA	51.24%	71.90%	60.77%	5.47E+00
	WOA	46.28%	69.42%	57.05%	5.77E+00
	DE	45.45%	72.72%	58.23%	7.33E+00
Dataset 2	EFA	38.01%	64.46%	52.61%	6.81E+00
	PSO	39.66%	61.15%	49.53%	5.46E+00
	SSA	37.19%	61.98%	50.49%	5.51E+00
	WOA	40.49%	58.67%	49.14%	5.20E+00
	DE	41.32%	61.98%	49.33%	4.81E+00
Dataset 3	EFA	71.88%	93.19%	83.02%	4.87E+00
	PSO	65.30%	86.16%	77.01%	5.87E+00
	SSA	69.84%	89.79%	80.81%	4.67E+00
	WOA	67.12%	90.47%	78.99%	5.83E+00
	DE	70.74%	89.11%	79.94%	4.74E+00
Dataset 4	EFA	79.70%	96.04%	89.01%	4.02E+00
	PSO	74.81%	93.96%	85.79%	5.01E+00
	SSA	74.19%	94.79%	88.86%	4.38E+00
	WOA	75.65%	95.10%	86.39%	5.07E+00
	DE	75.85%	95.62%	88.03%	4.79E+00

ANOVA Table

Source	SS	df	MS	F	Prob>F
Columns	744.6	4	186.151	4.67	0.0014
Error	5773.91	145	39.82		
Total	6518.52	149			

Fig. 9. Results of Dataset 1 ANOVA test.

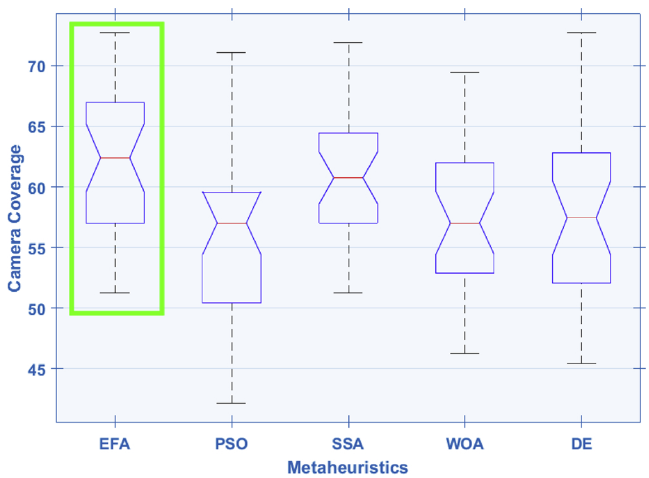

Fig. 10. Box plot of Dataset 1 ANOVA test.

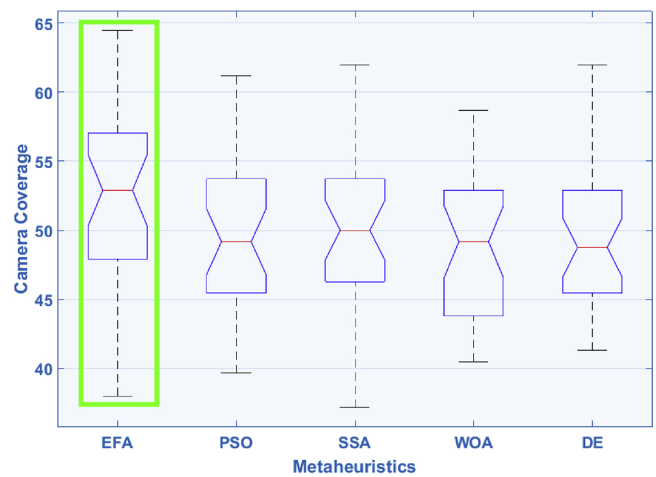

Fig. 12. Box plot of Dataset 2 ANOVA test.

$$fitness = \frac{number\ of\ covered\ grids}{total\ number\ of\ grids} \tag{10}$$

The generated new angles orient PTZ cameras through the production of vectors $\vec{x}$ and $\vec{y}$ that define the camera effective angle with the rotation matrix as (Slabaugh, 1999):

$$\begin{bmatrix} \vec{x}_r \\ \vec{y}_r \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} \vec{x} \\ \vec{y} \end{bmatrix} \tag{11}$$

where $\vec{x}_r$ and $\vec{y}_r$ are the new rotated vectors (see Fig. 6).

4.3. Enhancement

In this subsection, the proposed enhancement of FA is discussed.

4.3.1. Chaos driven FA with attractive search space border points

The proposed enhancement mainly focuses on the improvement of FA exploration. i.e. it helps FA to prevent premature convergence and escape from local solution. The strategy of chaos driven algorithm with attractive search space border points first was introduced by (Pluhacek, Senkerik, Viktorin, Kadavy, & Zelinka, 2018) which blended with PSO. In this paper, the previous strategy is selected to firstly be integrated with FA. Mainly, this strategy is based on partial attraction of solution to border points by a predefined percentage. Thus, the proposed algorithm attracts the orientation of PTZ cameras towards border points which can increase the area coverage. Instead of the Eq. (9), the new solution will be computed as:

$$x_{i+1} = \begin{cases} x_i + I_0 e^{-\gamma r^2} \varepsilon_1 (LowB - x_i) + \alpha \varepsilon_2 r_2 \le 0.5 \\ x_i + I_0 e^{-\gamma r^2} \varepsilon_1 (UpperB - x_i) + \alpha \varepsilon_2 r_2 > 0.5 \end{cases} \tag{12}$$

where $LowB$ and $UpperB$ are the lower and upper bound of the search space, respectively. r_2 is a uniform random number between [0,1].

4.3.2. Chaotic maps

Chaotic maps are evolution functions which can generate random numbers with a different time domain (continuous or discrete) such as Logistic map, Tent map, and Lozi map, etc (Devaney, 2018). It is mainly characterized by being nonlinear, deterministic, irregular, sensitive to initial conditions, impossible long term prediction. Therefore, they can ensure high stochasticity and convergence rate of the proposed algorithm. After several trials, Lozi map is selected to hybrid with EFA. The random numbers of Lozi map can be generated as follows (Sprott, 2003):

ANOVA Table

Source	SS	df	MS	F	Prob>F
Columns	246.77	4	61.6921	1.97	0.1026
Error	4546.82	145	31.3574		
Total	4793.59	149			

Fig. 11. Results of Dataset 2 ANOVA test.

ANOVA Table

Source	SS	df	MS	F	Prob>F
Columns	591.8	4	147.95	5.42	0.0004
Error	3956.58	145	27.287		
Total	4548.38	149			

Fig. 13. Results of Dataset 3 ANOVA test.

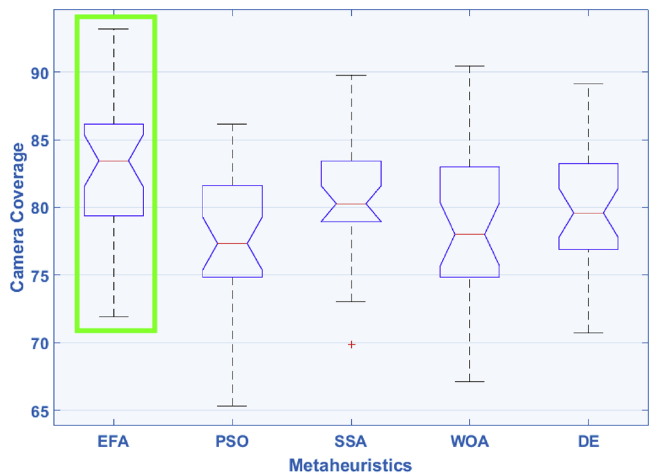

Fig. 14. Box plot of Dataset 3 ANOVA test.

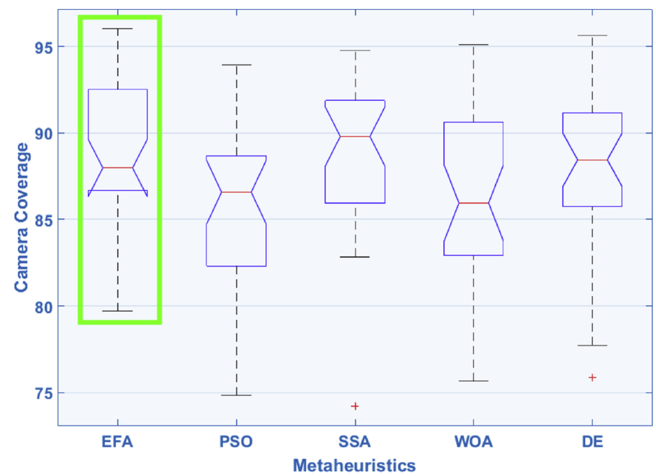

Fig. 16. Box plot of Dataset 4 ANOVA test.

$$X_{n+1} = 1 - a\ |X_n| + bY_n \tag{13}$$

$$Y_{n+1} = X_n \tag{14}$$

where X and Y are the set of coordinates in the two-dimensional space. a and b are predefined parameters. In the proposed algorithm, ε_1 in equation (12) with a random number drawn from Lozi map (see Fig. 7). Fig. 8 represents an illustration of the proposed algorithm.

5. Validation experiments & results

In this subsection, firstly the proposed algorithm is tested on many datasets that represented in Table 1. Secondly, EFA is applied in a selected practical case study. All the algorithms are coded in MATLAB© 2015. All experiments are carried out on a 64-bit operating system with a 2.60 GHz CPU and 6 GB RAM. EFA is tested on the four constructed datasets and compared with Particle Swarm Optimization (PSO) (Xu et al., 2011), Differential Evolution (DE) (Storn & Price, 1997), Whale Optimization Algorithm (WOA) (Mirjalili & Lewis, 2016), and Salp Swarm Algorithm (SSA) (Mirjalili et al., 2017). For all algorithms, the total number of iterations is set to 50 and the number of search agents is set to 10. The other algorithms parameters are listed in Table 2. In order to obtain fairly statistical results, each algorithm runs for 30 independent runs. Table 3 shows all descriptive statistics of the experiments. Generally, for all datasets, the proposed algorithm achieves the best mean value which indicates that it obtains much better results in the 30 run. For dataset 1, EFA achieves the highest mean value. While the worst coverage value of EFA is similar to SSA and its best coverage value is similar to DE. For dataset 2, EFA achieves the highest best and mean values while DE achieves the highest worst coverage value. For dataset 3 and 4, EFA achieves the highest worst, best, and mean coverage values. Regarding Standard Deviation (SD), the SD

Table 4
Wilcoxon Signed Ranks Test of Dataset 1.

Ranks		N	Mean Rank	Sum of Ranks
PSO - EFA	Negative Ranks	22[a]	16.41	361.00
	Positive Ranks	6[b]	7.50	45.00
	Ties	2[c]		
	Total	30		

[a] PSO < EFA.
[b] PSO > EFA.
[c] PSO = EFA.

ANOVA Table

Source	SS	df	MS	F	Prob>F
Columns	253.62	4	63.4062	2.91	0.0238
Error	3163.71	145	21.8187		
Total	3417.34	149			

Fig. 15. Results of Dataset 4 ANOVA test.

Table 5
Statistics of Wilcoxon Test on Dataset 1.

Test Statistics[a]	
	PSO - EFA
Z	−3.601[b]
Asymp. Sig. (2-tailed)	.000

[a] Wilcoxon Signed Ranks Test.
[b] Based on positive ranks.

Table 6
Wilcoxon Signed Ranks Test of Dataset 2.

Ranks				
	N	Mean Rank	Sum of Ranks	
PSO - EFA	Negative Ranks	16[a]	16.69	267.00
	Positive Ranks	11[b]	10.09	111.00
	Ties	3[c]		
	Total	30		

[a] PSO < EFA.
[b] PSO > EFA.
[c] PSO = EFA.

Table 7
Statistics of Wilcoxon Test on Dataset 2.

Test Statistics[a]	
	PSO - EFA
Z	−1.877[b]
Asymp. Sig. (2-tailed)	.061

[a] Wilcoxon Signed Ranks Test.
[b] Based on positive ranks.

Table 8
Wilcoxon Signed Ranks Test of Dataset 3.

Ranks				
		N	Mean Rank	Sum of Ranks
PSO - EFA	Negative Ranks	25[a]	15.44	386.00
	Positive Ranks	4[b]	12.25	49.00
	Ties	1[c]		
	Total	30		

[a] PSO < EFA.
[b] PSO > EFA.
[c] PSO = EFA.

Table 9
Statistics of Wilcoxon Test on Dataset 3.

Test Statistics[a]	
	PSO - EFA
Z	−3.644[b]
Asymp. Sig. (2-tailed)	.000

[a] Wilcoxon Signed Ranks Test.
[b] Based on positive ranks.

values of EFA are not the lower values which indicate the high stochasticity of EFA. However, the SD value of EFA for dataset 4 is the lowest which indicates the stability of EFA for such a difficult dataset. It is clear that the performance of all comparators seems to decline with

Table 10
Wilcoxon Signed Ranks Test of Dataset 4.

Ranks				
		N	Mean Rank	Sum of Ranks
PSO - EFA	Negative Ranks	24[a]	15.46	371.00
	Positive Ranks	6[b]	15.67	94.00
	Ties	0[c]		
	Total	30		

[a] PSO < EFA.
[b] PSO > EFA.
[c] PSO = EFA.

Table 11
Statistics of Wilcoxon Test on Dataset 4.

Test Statistics[a]	
	PSO - EFA
Z	−2.849[b]
Asymp. Sig. (2-tailed)	.004

[a] Wilcoxon Signed Ranks Test.
[b] Based on positive ranks.

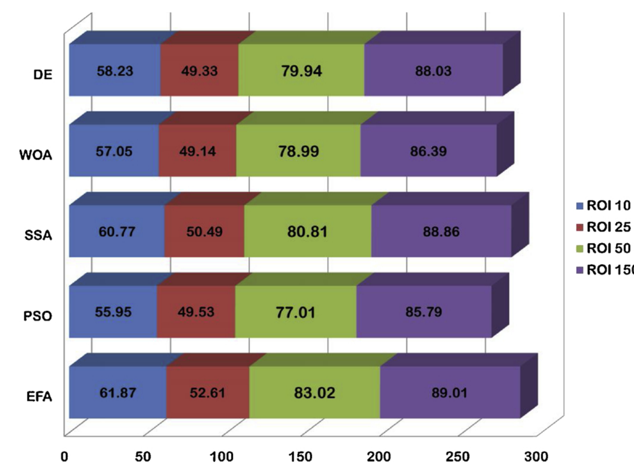

Fig. 17. The Mean of Cameras Values in Different ROI.

the increasing difficulty of datasets and this is clear from their obtained values.

5.1. One-way ANOVA test

Furthermore, One-way ANOVA Test (Tarlow, 2015) is conducted for analyzing the performance of the proposed algorithm against the compared ones. The ANOVA, developed by Ronald Fisher in 1918 (Elston, 2018), extends the t and the z test which have the problem of only allowing the nominal level variable to have two categories. This test is also called the Fisher analysis of variance. A one-way ANOVA is a statistical technique that assesses potential differences in a scale-level dependent variable by a nominal-level variable having 2 or more categories with just one independent variable. In other words, one-way ANOVA can determine that at least two groups are different from each other. Although, it can't determine which groups are different. If one-way ANOVA returns a significant f-statistic, it is needed to make a post-hoc hypotheses test to determine exactly which groups have a difference in means (Giri, 2019). The null hypothesis for this test is that the means are equal. The value of α is set to 0.05. The obtained results with p-values for all datasets are given in Figs. 9, . It is clear that the null

Fig. 18. The New Administrative Capital (CUBE, 2018).

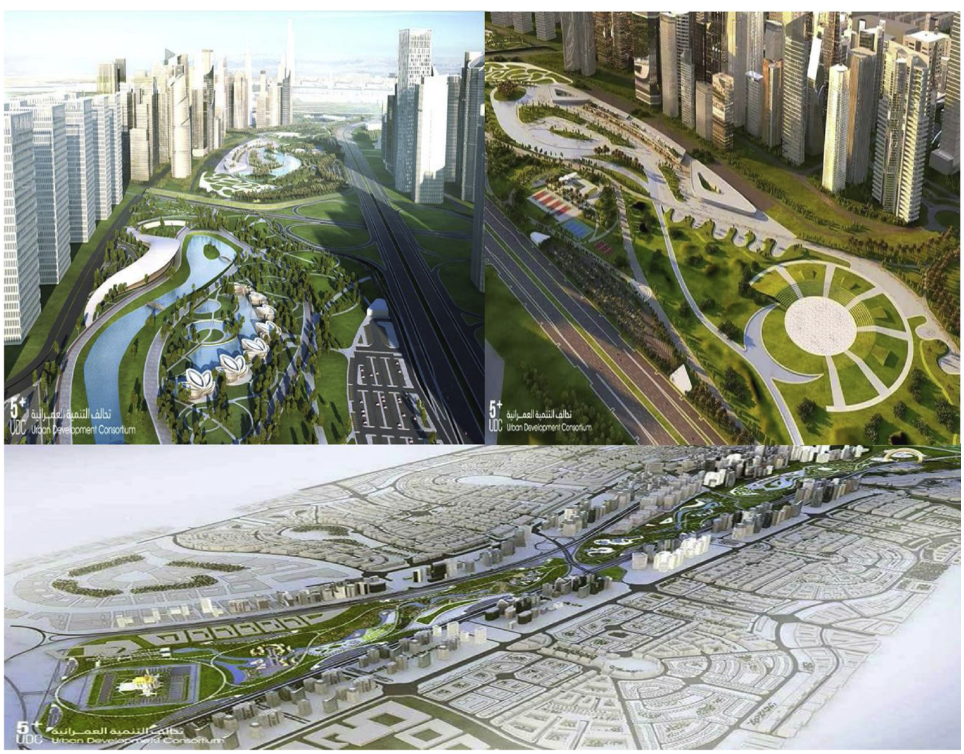

Fig. 19. Green River in Egypt (MoHUUC, 2018).

hypothesis is rejected while the research hypothesis is accepted as all p-values are fewer than α except for dataset 2. Figs. 10, 12, 14, and 16 show the box plot of the ANOVA analysis for each dataset, respectively. It is clear that the box of the proposed algorithm is higher than others and its median (the middle red line) indicates that it efficiently obtains higher coverage values. Again for all other comparators, their boxes decline with the increasing difficulty of datasets and are trapped into a local optimum.

5.2. EFA and PSO paired analysis

PSO can be considered a special case of FA (Yang, 2017). In addition, PSO is the most popular algorithm for solving cameras network coverage problem. Thus, EFA and PSO are analyzed with Wilcoxon sign test (Haynes, 2013) in order to conduct a detailed comparison between them. The signed ranks results are presented in Tables 4, . The number of positive differences is lower than the negative differences for the

Fig. 20. Seven Central Parks of Green River in Egypt (MoHUUC, 2018).

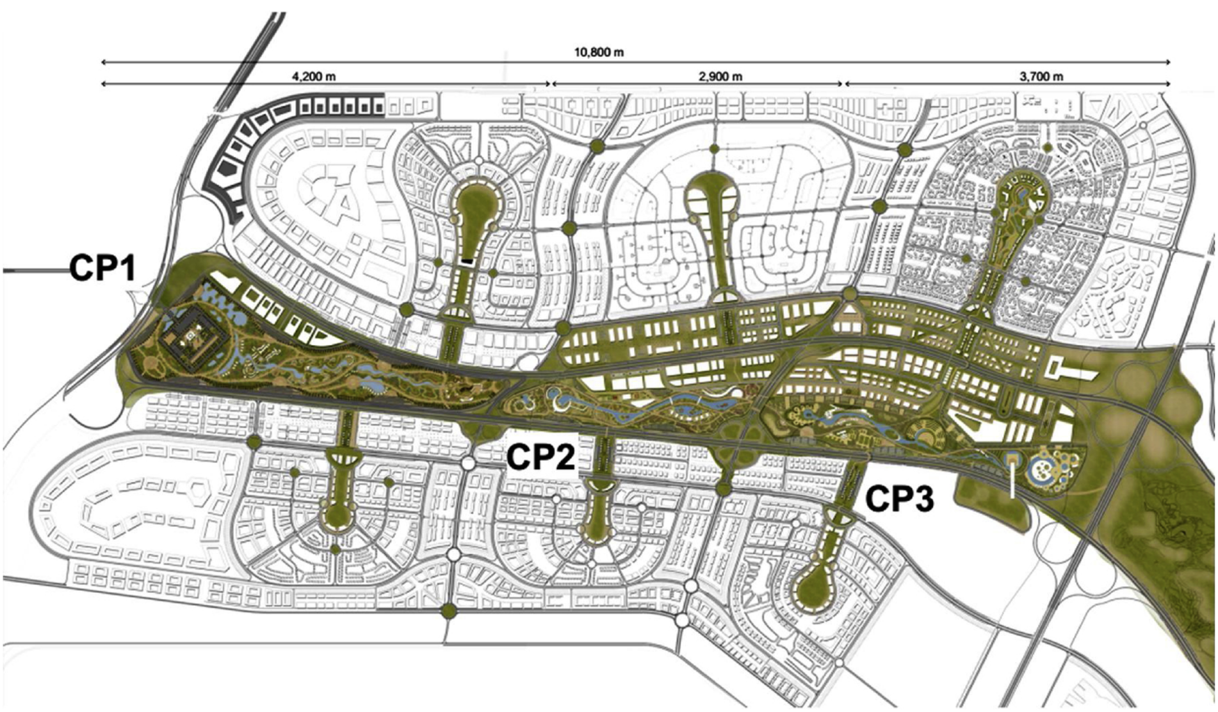

Fig. 21. Phase One of Green River in Egypt (MoHUUC, 2018).

Table 12
CP2 and CP3 Problem Formulation.

Central Park	Height	Width	Expected Coverage Calculation	Number of PTZ Cameras	PTZ camera Infra-Red radius	The total ROI area
CP2	2900 m	300 m	$1-\left(1-\frac{\frac{\pi}{4}\times 120^2}{2900\times 300}\right)^{50} \cong 0.\ 4802$	50	120 m	870 km^2
CP3	3700 m	500 m	$1-\left(1-\frac{\frac{\pi}{4}\times 120^2}{3700\times 500}\right)^{100} \cong 0.4584$	100	120 m	1850 km^2

Table 13
Descriptive statistics of EFA for CP2 and CP3 Problem.

Central Park	Expected Coverage	EFA Coverage			
		Worst	Best	Mean	SD
CP2	48.02%	57.26%	85.73%	74.74%	7.61E+00
CP3	45.84%	64.01%	87.58%	77.91%	6.20E+00

dataset 1 to dataset 4 which means that all EFA coverage values are greater than PSO values. In addition, the tie cases are diminutive even it is equal to zero in dataset 4. The statistics of Wilcoxon Test are given in Tables 5, 7, 9, and 11. The p-values of the dataset 1, dataset 3, and dataset 4 are lower than 0.05. Thus, there are significant differences between the tested values. While the p-value of dataset 2 is greater than 0.05 which indicates that there are no significant differences between the tested values.

5.3. Discussion

In the original FA, the randomization typically uses uniform distribution or Gaussian distribution. In this paper, a border attractive mechanism is combined with FA search procedures in order to increase convergence and exploration. In other words, one of the challenges facing the area coverage problem is the bulking inside ROIs. Attractive border mechanism pulls cameras FOV towards a ROI border with a predetermined percentage. For more randomness, switching between upper and lower limits is done randomly with an equal percentage which obviously affects the performance of the proposed algorithm. By studying the impact of improvements on FA, it proves that it can effectively cover ROI with a larger area and a low number of cameras. As shown in Fig. 17, when the proposed algorithm and the comparators are applied on dataset1 and dataset2, it is found that there is no large difference between algorithms coverage percentages. For dataset3 and dataset4, the proposed algorithm is able to reach promising coverage percentages.

6. Case study: “the Green River in the new administrative capital in Egypt”

Egypt is entering a new smartness and technological century via releasing its new administrative capital "New Cairo". The New Capital Cairo is a new smart city that has been constructed to be an extension of the current capital. It extends 45 Km away from Cairo and 60 Km from Suez city. The city is destined to host 7 million inhabitants on a total area of 170,000 acres / 714 Km^2 that making it larger than Washington D.C (CUBE, 2018). The new smart city will contain 100 districts that will host the governmental institutions and the seats of different ministries as well as a district for the diplomatic representation of the different international embassies. Also, it will contain 21 housing residential areas with a regional park for healthcare and recreational purposes (Serag, 2017) (See Fig. 18). The most important characteristic of the new capital Cairo is the green lifestyle that comes with the Green River.

6.1. Green River

Green River can be considered the Nile River of the new administrative capital. In other words, it was decided to replace the Nile River with a green river of gardens with a length of 35 sqm and 5000 acres what makes it one of the biggest gardens all over the world (See Fig. 19). It is like a "lung" to purify the atmosphere and make it an ecologically integrated city enjoying fresh air throughout the day. Unlike old Cairo, the capital needs 12 million trees to overcome the air problems and toxic air pollution that cause death to many adults and young people. In addition, the green river will connect all universities, districts, and cities in the new smart capital so that residents can reach the main park on foot with free of charge visits. The green river consists of seven Central Parks (CPs) (Murabahat, 2018):Gate and Historical Park (CP1), Sustainability Park (CP2), Civil Park (CP3), International Park (CP4), Science and Technology Park (CP5), Health Park (CP6), and Nature and Wild Life Park (CP7) (See Fig. 20).

6.2. Problem formulation

As shown before, the proposed design scheme of Green River of the administrative capital assumes that it has a length of 35 Km^2. The first phase, which already has been built, has a length of 14 km that dedicated from 300 m to 1500 m. It includes distributed activities supporting the collective and vital clearance of the greater Cairo area, the adoption of irrigation green river gardens on the abortion of sewage from neighboring cities until the city completed, and extends the full range of cultural, social, sports and commercial activities. To sum up, the first phase consists of (CUBE, 2018) (see Fig. 21):

- CP1with an area of 595 acres, of the most important components are gates, entrances, and mosque.
- CP2 with a total area of 250 acres, the most important component is sustainability park with fruitful gardens.
- CP3 with a total area of 515 acres, the most important components are lake area, playground area, grand arena area, and open theater area.

CP1 includes gates and entrances which obliges surveillance cameras to be allocated into specific locations. As a consequence, this paper proposes a surveillance system for CP2 and CP3 via CCTV camera network that optimized with EFA. For PTZ cameras network, the available PTZ cameras in Egypt has distance coverage approximately ranging from 15 to 150 m (forecast). According to the importance of the monitored location, cameras with 120 m Infra-Red range are selected. Table 12 the mathematical specification of two CPs. For the proposed algorithm, the total number of iterations is set to 50 and the number of search agents is set to 10. For calculating statistics, EFA runs for 30 independent runs. The other algorithm parameters remain as previous. Table 13 shows the descriptive statistics of EFA results of CP2 and CP3. The high value of SD indicates the high randomness of the proposed algorithm.

6.3. Implications of practice

After performing the appropriate statistical analysis, the proposed algorithm is applied to the problem of adjusting cameras orientation in CP2 and CP3 in the new smart capital of Egypt. By investigating the prices of PTZ cameras available in Egypt, a PTZ camera with 120 m Infra-Red range costs approximately 10,000 LE which approximately equivalent to 500 $. In Table 14, the benefit of EFA for reducing the

Table 14
The implication in surveillance cameras cost when applying EFA.

Central Park	Expected Coverage	Reached coverage by EFA	Difference	Number of saved cameras	Saved costs
CP2	48.02%	85.73%	37.71%	37	18,500 $
CP3	45.84%	87.58%	41.74%	89	44,500 $

surveillance cost is represented. As shown, EFA is able to reduce the number of used cameras for monitoring CP2 and CP3. As a consequence, the cost needed for PTZ is obviously reduced. The number of cameras with respect to coverage can be calculated as (Erdem & Sclaroff, 2004):

$$N = \frac{\ln(1 - cov)}{\ln(\mathrm{A(ROI)} - \varphi r^2) - \ln\mathrm{A(ROI)}} \tag{15}$$

where cov is the total cameras coverage of ROI.

7. Conclusions

The quality of any surveillance system is determined by the coverage of the cameras network consolidation. This paper proposes a new enhanced AI algorithm in order to optimize the coverage of PTZ cameras network. In particular, the original FA algorithm is hybrid with chaotic Lozi map and the mechanism of attractive search space border points. In Addition, the determination of coverage percentage is performed by grid-based separation of ROI. This method of calculating the solution fitness is more accurate and appropriate for all FOV shapes. The proposed algorithm is compared with other artificial intelligence algorithms. The experimental results indicate the efficiency and consistency of the proposed algorithm. This is proved by the one-way ANOVA statistical analysis which shows that the median value of the proposed algorithm is better than other comparators. Also, it is compared with PSO algorithm. The experimental results are analyzed with Wilcoxon signed-rank test. The experimental results and the statistical analysis prove the efficiency of the proposed algorithm. In addition, the proposed algorithm is applied to adjust the orientation of CCTV cameras in CP2 and CP3 of the green river in Egypt. The proposed algorithm is able to increase the cameras network coverage and reduce the surveillance set up costs.

7.1. Limitations and future research directions

Although the efficiency of EFA, there are some limitations. Firstly, the proposed algorithm is not considering more metric to determine the best camera orientation such as ROI environment. Secondly, the case of obstacles appearance is not covered in this work. Thirdly, when the search space becomes larger and larger, the time cost of the proposed algorithm become very high. Thus, it is better in such a case to use parallel computing with machine learning (Martins, 2018).

For future work, we suggest applying the proposed algorithm to other types of coverage problem in different application fields like traffic surveillance. EFA can be used for solving other cameras network-related problems such as data aggregation, allocation, and energy preservation, etc. Also, there are several enhancements can be made to the proposed algorithms such as the fuzzy logic that can be used for determining the algorithm parameters.

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