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RESEARCH ARTICLE

Dynamic Target Search Using Multi-UAVs Based on Motion-Encoded Genetic Algorithm With Multiple Parents

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ABSTRACT In this paper, a new optimization algorithm called Motion-Encoded Genetic Algorithm with Multiple Parents (MEGA-MPC) is developed to locate moving targets using multiple Unmanned Aerial Vehicles (UAVs). Bayesian theory is used to formulate the moving target tracking as an optimization problem where target detection probability defines the objective function as the probability of detecting the target. In the developed MEGA-MPC algorithm, a series of UAV motion paths encodes the search trajectory. In every iteration of the MEGA-MPC algorithm, UAV motion paths undergo evolution. The proposed approach for dynamic target search using multi-UAVs uses parallel computations to solve the optimization problem based on the MEGA-MPC algorithm where Each UAV can communicate with other UAVs if requested. The algorithm's performance is tested with various characteristics under six distinct scenarios using a different number of UAVs and targets. The statistical analysis of the results obtained using MEGA-MPC compared with other well-known metaheuristics shows that MEGA-MPC offers better solutions to find dynamic targets since it outperforms all the compared algorithms.

INDEX TERMS Dynamic target search, motion-encoded genetic algorithm, probabilistic targets, unmanned aerial vehicles.

I. INTRODUCTION

Technological advancements have resulted in the widespread adoption of unmanned aerial vehicles (UAVs) in various aspects of human endeavour. Drones are now commonly applied in search, rescue, reconnaissance and surveillance tasks. UAVs are intensely adaptable, capable of working in diverse environments, affordable and efficient in following commands and intercommunication. The widespread application, capabilities, coordination improvements, and other features have made the research area promising. Therefore, UAVs are very widely and successfully used in application fields like target detection [1], object tracking [2], map building, [3], [4], environmental building [5], and so on.

Different factors need to be carefully considered in a UAV-based target search problem. One of those is to identify the duration over which the probability of finding the target is maximum [6]. Above this critical period, getting the job done becomes difficult due to weather, deviation from the initial trajectory, terrain characteristics, and other factors. Therefore, in designing a search problem formulation with UAVs, there is the need to consider both the drone flight path

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trajectory and flight time. Works have been done on trajectory problem formulation where the UAVs flight trajectories are considered in real-time over a prediction horizon [2]. Another critical issue of designing such problems is the availability of initial information about the target position, besides other search conditions [7], [8]. A common approach is to account for uncertainty by modelling the initial conditions using some probability function. There is also the need to diligently account for sensor models and other search conditions and constraints.

In searching for lost targets, either a single or multiple UAVs could be employed. For the multi-UAV case, coordination between the vehicles plays a crucial role in increasing the efficacy of the search mechanism especially in the case of finding multiple targets at the same time. However, there are several challenges in such cooperative search problems [9]. One of such challenges is ensuring that individual UAVs can function autonomously, irrespective of their communication and sensing capabilities. Besides, the design should be robust enough to cope with different harsh situations while fulfilling practical constraints.

A Bayesian approach for the target search problem was proposed in [7], [10] to evaluate the probability of a UAV flight path. In [8], [11], the target dynamics was formulated as a stochastic Markov process which has a deterministic characteristic of not being affected by the searching scenarios. The search map was modelled as a multivariate and normal distribution where the initial target position determines the mean and variance of the distribution [11], [12]. On a different note, a Kalman filter-based optimization model was adopted in [13], where it combines observations from different sensors. In [14], an optimal path planning mechanism, which works with the central Voronoi partitioning algorithm, was proposed. In a collaborative search problem, a self-assessment based method [15] that was applied to different communication structures was adopted. The adopted approach has been very efficient in scalability, communication and design complexity. In [14], the search problem is formulated as a parallel control system where converge control, data source detection, and data collection procedures can work simultaneously. However, in most of these collaborative search problems, the UAVs that participated in the search process were assumed to be homogeneous, reducing the effects of external obstacles. Reference [16] utilizes a game-theory based method for cooperative research and contrasted results with modified binary log-linear learning. However, an improved multi-ant colony scheme is used in unknown environments for multi-UAVs search in [17].

The presence of multiple probabilistic variables increases the complexity of these search problems. The resulting non-deterministic problems could either have a polynomial-time hardness [8] or exponential-time complexity, as the case may be. Therefore, classical methods like differential calculus are non-suitable and impractical to use in such scenarios. Consequently, different heuristic optimization algorithms like Genetic Algorithm (GA) [18], Ant Colony Optimization (ACO) [12], one-step look ahead greedy search algorithm [7], k-step look ahead greedy search algorithm [8], Bayesian optimization approach (BOA) [10], branch and bound approach [19], Cross Entropy Optimization (CEO) [20], gradient descend methods [21], [22], limited depth search algorithm [23] etc. are tried and found considerably efficient on such UAV-based search problems. Among the tried methods, [10], [12], [20], [23] presented the algorithms which can handle multiple UAVs for search operations, resulting in a fast-paced search process. On the contrary, [7], [8] proposed the algorithms where the design specifications of the search problem are the main focus.

It is noteworthy to mention that most of the approaches discussed above used the binary model of sensor detection to track the moving targets effectively. Recently, [24] proposed the motion-encoded particle swarm optimization (MPSO) for solving the given search problem using one UAV. The paper presented the comparative results with some famous heuristic approaches showing that the developed method is 4.71 times more time-efficient with 24% high detection accuracy than the default PSO. Reference [25] reviews various intelligent optimization algorithms tested on swarm search applications involving UAVs. Because of the high complexity of the search problem, particularly in the case of fast-moving targets and multiple UAV presence, the optimization problem formulation and its solution strategy become more challenging. On the flip side, the recent advancements in UAV technologies, sensors manufacturing, and communication infrastructure have kept the window of advanced research in the field and finding better solutions open. The solution mechanism of the target search problem needs to be robust in terms of search capacity. It also needs to possess the properties of methodical optimization tools such as adaptability, computational efficiency and optimality. On the optimization front, joint optimization of multi UAV path planning and target assignment has been carried out by multi-agent reinforcement learning in [26].

Furthermore, with the advance in computing performance of new computers, many optimization algorithms have been developed in the field of metaheuristics. For example, in [27], a new optimization metaheuristic based on ancient war strategy is proposed. This algorithm is called War Strategy Optimization (WSO) and it mimics the strategic movement of army troops during the war. The proposed algorithm is tested using a 50 benchmark test functions and compared with several algorithms. The results are encouraging for future use of this algorithm. Another example is the Jaguar Algorithm (JA) which is based on the behaviour of jaguars in the wild. This algorithm is proposed in [28]. The proposed algorithm is tested over Seven classic benchmark function problems and compared with couple of algorithms. The results show the good performance of this algorithm. In [29] a new metaheuristic called Crystal Structure Algorithm (CryStAl) which is inspired by the principles underlying the formation of crystal structures from the addition of the basis to the lattice points is proposed. The performances of the proposed algorithm are tested over 239 mathematical functions and compared with 8 well-known optimization algorithms. The results of the proposed CryStAl have been found to be better than the remaining comparing algorithms. A multi-objective version of the is which is called MOCryStAl is proposed in [30]. Another very interesting work is presented in [31]. The authors of this work proposed a new Parallel Hybrid Island architecture which shows a parallel way to combine different metaheuristics by using the island model as the base. Using the proposed approach several combinations of metaheuristics has been made with better performance than single algorithms.

As the optimization tool for the considered problem, this paper has proposed a GA with Multiple Parents (GA-MP) [32] and motion encoding (ME) feature. In GA, multiple parents take part in the recombination phase. The GA-MP mechanism combines these parents based on diagonal crossover and gene scanning. This approach improves the efficacy of the conventional GA in searching for the global optima. This promising optimization algorithm has been tested and checked with diverse optimization problems like constrained optimization, graph coloring and numerical optimization, and compared with several state-of-the-art algorithms [32], [33]. Moreover, the motion encoding feature is added to GA-MP for the first time in this paper to boost the algorithm's search capabilities.

This article presents the Motion-Encoded Genetic Algorithm with Multiple Parents (MEGA-MP) as a solution tool for searching the dynamic targets, with multiple UAVs coordinated for improved performance. The key features of this work are as follows:

- The formulation of the moving target search task as an optimization problem by defining the objective function and associated constraints for accurate tracking.
- Implementation of the motion encoding (ME) mechanism with GA and Multiple Parents (GA-MPC) for the first time to form a combined optimization tool to deal with the optimization problem with good results.
- The use of multiple UAVs with or without communication to track one or multiple targets at the same time.
- Investigation of six scenarios with different complexities to asses the performance of the proposed algorithm.
- Comparison of the obtained results with 10 other popular and state-of-the-art optimization algorithms to check the suitability of the proposed algorithm in the application of interest.

The rest of the paper has been organized as follows: the problem formulation of moving object tracking with multiple coordinated UAVs has been presented in this section. The formulation of the objective function and associated constraints are presented in section II. Section III describes the optimization tool proposed in this paper: the Motion-Encoded Genetic Algorithm with Multiple Parents (MEGA-MP). Section IV describes the simulation results and discusses the optimization algorithms used for comparison. Lastly, section VI concludes the article.

II. PROBLEM FORMULATION

This section gives a detailed account of the searching problem, including target and senor models, and belief map similar to the presentation [12] and [34].

A. TARGET MODEL

The searching problem always begins with the assumption of an appropriate probability distribution function (PDF). The purpose of the PDF is to model the target's location subject to its most recently available information, for example the last known location before signal is lost. More details on location probability estimation can be found in [35], [36]. A Normal or Gaussian distribution, for instance, could be used if there is information about the target location; otherwise, a uniform distribution will be suitable. Let represent the searching area by Ω and the unknown location in the search problem by ν^t. To model the initial probability map, we discretize Ω into a 2−dimensional grip whose $\Omega_x \times \Omega_y$ cells can be uniquely identified by their indexes. Given the initial observation ψ_0, let represent the probability function by a grip-based map $p\left(\nu_0^t|\psi_0\right) = b(\nu_0^t)$ called initial belief map or priori PDF. Each cell in $b(\nu_0^t)$ corresponds to a discretization of the search area with an associated probability that the target is present in that cell. Since $\nu_0^t \in \Omega$, by applying the well-known property of probability distribution, we have

$$\sum_{\nu_0^t \in \Omega} b(\nu_0^t) = 1. \tag{1}$$

Markov Process is used to model target navigation pattern, in particular, if the target is not static. For a conditionally deterministic target, such that its movement pattern depends on the target's first location, ν_0^t, the Bayesian approach is employed. In this instance, the probability that the target proceeds from cell ν_{k-1}^t to ν_k^t is given by $p(\nu_k^t|\nu_{k-1}^t)$. Accordingly, for a known initial position, the target's entire path will be known. This procedure is a well-known assumption in target search problems. The interested reader can find more information in the following references [10], [12], [37].

B. SENSOR MODEL

We assume that independent measurements ψ_k are made by the only sensor attached to the UAV at time step t through a sensor model given by

$$p\left(\psi_k = D_k|\nu_k^t,\ \varphi_k\right), \tag{2}$$

where ν_k^t and φ_k are the target and UAV positions, respectively. The observations are independent because their occurrence gives no information concerning the occurrence of other observations. The function (2) represents the probability of the target detection $\psi_k = D_k$ subject to ν_k^t and φ_k. Detection algorithm classifies the measurement, which is either a detection $\psi_k = D_k$ or no detection $\psi_k = \overline{D}_k$. Consequently, given a target location ν_k^t, the probability of no detection is obtained using

$$p\left(\psi_k = \overline{D}_k|\nu_k^t,\ \varphi_k\right) = 1 - p\left(\psi_k = D_k|\nu_k^t,\ \varphi_k\right). \tag{3}$$

In an ideal sensor, for instance, the target is only detected when $\nu_k^t = \varphi_k$. In this case, we have

$$p\left(\psi_k = D_k | \nu_k^t,\ \varphi_k\right) = \begin{cases} 1, & \text{if } \nu_k^t = \varphi_k \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

C. BELIEF MAP UPDATE

After establishing the prior PDF $p\left(\nu_0^t | \psi_0\right) \equiv b(\nu_0^t)$ as explained in subsection II-A and given the sequence of observations $\psi_{1:k} = \{\psi_1 \cdots \psi_k\}$ made by the sensor, the Bayesian approach is used to recursively construct the belief map of the target state $p\left(\nu_k^t | \psi_{1:k}\right) \equiv b\left(\nu_k^t\right)$ at time step k. This method of iteration is called the Recursive Bayesian Estimation (see [7] for details) and it iterates through two stages; the prediction and update stages.

The prediction stage comes into play when belief map of the target fluctuates with time. Mathematically, suppose the belief map at time step $k-1$, that is $p\left(\nu_{k-1}^t | \psi_{1:k-1}\right) \equiv b\left(\nu_{k-1}^t\right)$, is known, then the predicted belief map at time step k, that is $p\left(\nu_k^t | \psi_{1:k-1}\right) \equiv \widehat{b}\left(\nu_k^t\right)$ is evaluated as follows:

$$\widehat{b}(\nu_k^t) = \sum_{\nu_{k-1}^t \in \Omega} p(\nu_k^t | \nu_{k-1}^t) b(\nu_{k-1}^t). \tag{5}$$

Recall that $b\left(\nu_{k-1}^t\right) \equiv p\left(\nu_{k-1}^t | \psi_{1:k-1}\right)$. So, it is the conditional probability of ν_{k-1}^t given that the sequence of observations up to $k-1$ are already known.

The update stage is binding when the observation at time step k, that is ψ_k, is available. Then, assuming all the observations are independent, the update is evaluated by multiplying the latest conditional observation by the predicted belief map given by (4). Mathematically, we have

$$b(\nu_k^t) = \lambda p(\psi_k | \nu_k^t) \widehat{b}(\nu_k^t), \tag{6}$$

where λ given by

$$\lambda = \frac{1}{\sum_{\nu_k^t \in \Omega} p(\psi_k | \nu_k^t) \widehat{b}(\nu_k^t)} \tag{7}$$

The parameter, λ, is a normalization factor employed to keep the target inside the search area. In other words, λ ensures

$$\sum_{\nu_k^t \in \Omega} b(\nu_k^t) = 1. \tag{8}$$

Useful information on how the belief map used in this work can be improved or changed is given in [38]

D. OBJECTIVE FUNCTION

This subsection focuses on formulation of the objective function represented by $\mathcal{F}$. Let us denote by $\tau_k \equiv p\left(\overline{D}_k | \psi_{1:k-1}^t\right)$ the conditional probability that a target does not get detected at time step k during a sensor observation. This τ_k across the entire searching area is the summation of the product of the probability of no detection given by (3) and the predicted belief map given by (5). Mathematically, we have Using (8) and bearing in mind the normalization factor given by (7) for no detection (i.e $\psi_k = \overline{D}$), it follows that $\lambda \tau_k = 1$. Consequently, τ_k is bounded between 0 and 1, that is, $0 < \tau_k \leq 1$. It is only zero when the probability that target proceeds from cell ν_{k-1}^t to ν_k^t is zero, that is, $p(\nu_k^t | \nu_{k-1}^t) = 0$, otherwise, it decreases as k increases, see [12]. It is obvious that $\tau_k = 1$ when the normalization factor is 1. Since all the observations are assume to be independent, it follows that the conditional probability that the target is detected at time step k is

$$1 - \tau_k. \tag{9}$$

The joint probability of failing to detect the target from steps 1 to k denoted by $\sigma_k = p\left(\overline{D}_{1:k-1}\right)$ is the product of all τ_k, that is,

$$\sigma_k = \prod_{i=1}^{k} \tau_i. \tag{10}$$

From (10), it follows that

$$\sigma_k = \tau_1 \tau_2 \tau_3 \cdots \tau_{k-1} \tau_k = \prod_{i=1}^{k-1} \tau_i \tau_k = \sigma_{k-1} \tau_k. \tag{11}$$

Consequently, by using (9) and (11), the probability that the target gets detected for the first time at step k can be evaluated as follows:

$$\rho_k = \sigma_{k-1} \left(1 - \tau_k\right). \tag{12}$$

Now, we compute the cumulative probability in k steps denoted by χ_k by summing over (12) as follows:

$$\chi_k = \sum_{i=1}^{k} \rho_i = \chi_{k-1} + \rho_k \tag{13}$$

Finally, based on (13), we formulate the objective function as follows. Define a search path $P = (p_1, p_2, \ldots, p_N)$ and let $\{1, 2, \ldots, N\}$ represents the time period. Searching strategy aids at finding P such that (13) is maximize. Thus, the search objective function is given as

$$\mathcal{J} = \sum_{k=1}^{N} \rho_k. \tag{14}$$

III. MOTION-ENCODED GENETIC ALGORITHM WITH MULTIPLE PARENTS (MEGA-MPC)

This section details the proposed Motion-Encoded Genetic Algorithm with Multiple Parents (MEGA-MPC) and its implementation in solving complex search problems.

A. GENETIC ALGORITHM

Genetic Algorithms (GA) are search algorithms inspired by the theory of evolution using the principles of genetics and natural selection. GA combines the survival of the fittest feature among its string structures with a structured but randomized information exchange to form a search algorithm with some of the innovative knacks of human search. GA, a universally adopted evolutionary algorithm for solving real-life

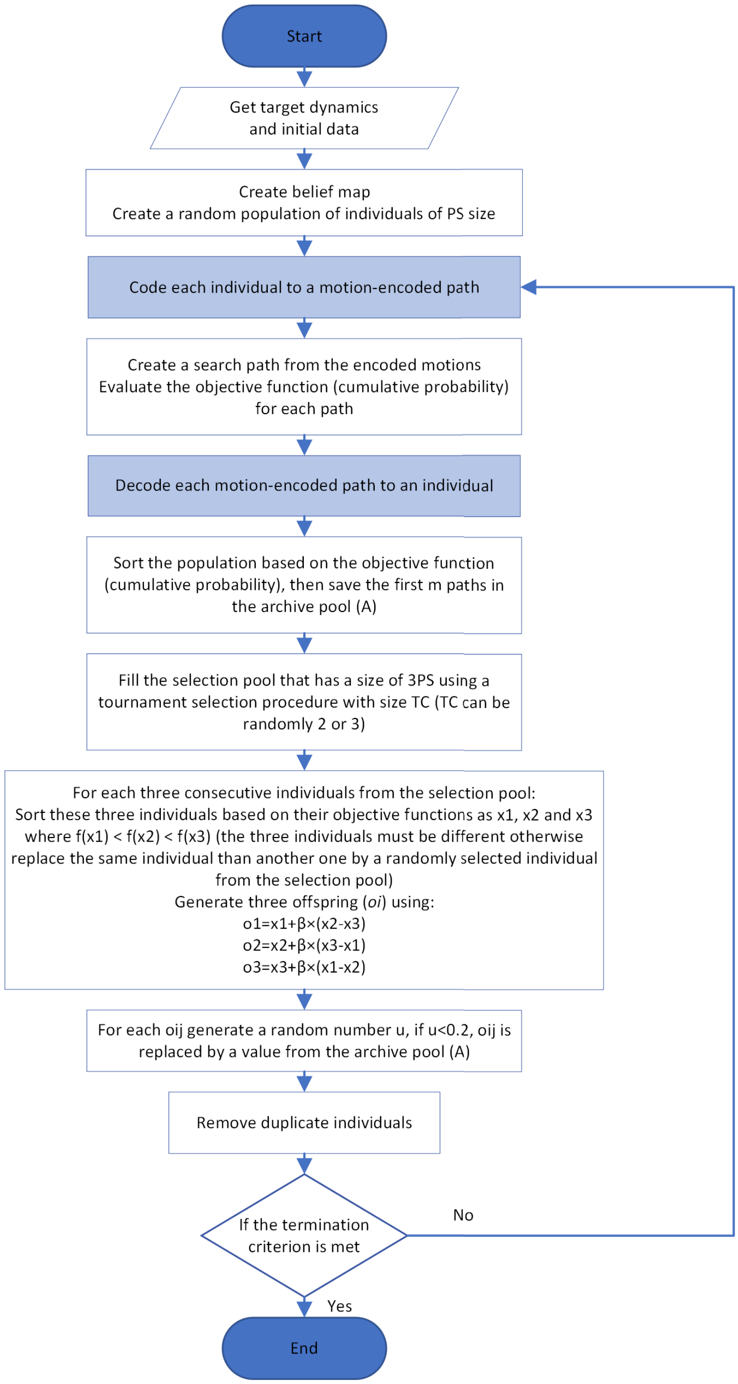

FIGURE 1. Flowchart of the proposed approach.

and practical optimization problems, can effortlessly deal with highly complex fitness landscapes. Additionally, It is very suitable for parallel computing. It adopts crossover and mutation as its primary search operators. However, various improvements have been considered over time to address the slow response and uncertainty for convergence to global optimal associated with traditional GA. In line with this fact, this work considers some modifications to the conventional GA for improved performance.

B. GENETIC ALGORITHM WITH MULTIPLE PARENTS (GA-MPC)

Various parent crossover methods have been proposed in the literature. Some of these methods include the Unimodal

TABLE 1. Comparing algorithms.

Algorithm name	Abbreviation	Main reference	Algorithm inspiration	Parameters
Most Valuable Player Algorithm	MVPA	[39]	Inspired from sports competition	number of players =90 and number of teams=20
Differential Evolution	DE	[40]	Based on evolutionary process	Population size = 90, differential weight = 0.8 and crossover probability = 0.8905
Motion-encoded Particle Swarm Optimization	MPSO	[24]	PSO algorithm's enhanced version based on ME mechanism	Population size = 90, inertia factor = 0.5, cognitive factor = 1.5 and social factor =1.5
Genetic Algorithm	GA	[32]	Inspired from Darwin's theory of evolution	Population size = 90, mutation rate = 0.05 and fraction of population kept = 0.75
Electrostatic Discharge Algorithm	ESDA	[41]	Inspired by the electrostatic discharge phenomena	Number of objects = 90
Biogeography-Based Optimization	BBO	[42]	Based on on biogeography, which covers the distribution and growth of living beings through space and time	Population size = 90, mutation probability = 0, habitat modification probability = 1 and initial mutation probability = 0.005
Artificial Bee Colony	ABC	[43]	Inspired from the foraging pattern of a bee swarm	colony size = 90 and number of food sources = 45
Gravitational Search Algorithm	GSA	[44]	Inspired from Newton's fundamental laws of motion	Number of agents = 90
Black Hole	BH	[45]	Inspired from the black hole theory	Number of stars = 90
Teaching-Learning-Based Optimization	TLBO	[46]	Inspired from the teaching-learning process	Class size =90
Since Cosine Algorithm	SCA	[47]	Motivated by the trigonometric sine and cosine functions	Number of search agents = 90

TABLE 2. Statistical analysis of the outcome of all algorithms for scenario 1.

	MEGA-MPC	MVPA	DE	PSO	GA	ESDA	BBO	ABC	GSA	BH	TLBO	SCA
BEST	0.22401	0.19581	0.22401	0.19768	0.1775	0.21541	0.21819	0.21544	0.21333	0.19716	0.22401	0.19727
MEAN	0.21209	0.11846	0.20313	0.06896	0.14718	0.15716	0.19749	0.16974	0.04558	0.14247	0.20358	0.17547
MEDIAN	0.21583	0.13728	0.19955	0.03519	0.14515	0.15779	0.20043	0.17426	0.00029	0.13861	0.20113	0.17545
WORST	0.19149	0	0.18308	0	0.11448	0.05155	0.13743	0.00142	0	0.07555	0.18679	0.14704
SD	0.00865	0.06646	0.0123	0.07188	0.01592	0.03122	0.01448	0.03699	0.06685	0.02701	0.00972	0.0116
FR	100	100	100	100	100	100	100	100	100	100	100	100
BEST	0.23285	0.17668	0.21899	0.14834	0.12443	0.1955	0.217	0.1586	0.13931	0.16621	0.22465	0.1712
MEAN	0.18639				0.04927						0.18389	
MEDIAN	0.19769				0.05907						0.19311	
WORST	0.00886				0						0	
SD	0.04068				0.03774						0.03903	
FR	100	87	90	50	100	93	90	17	30	97	100	93

TABLE 3. Statistical analysis of the outcome of all algorithms for scenario 2.

	MEGA-MPC	MVPA	DE	PSO	GA	ESDA	BBO	ABC	GSA	BH	TLBO	SCA
BEST	0.27905	0.26014	0.27466	0.22652	0.22486	0.23978	0.26156	0.24424	0.18925	0.23919	0.27689	0.25629
MEAN	0.26074	0.17272	0.24516	0.1067	0.18563	0.18328	0.21522	0.19452	0.05717	0.19299	0.25216	0.22412
MEDIAN	0.26356	0.19613	0.24909	0.11274	0.18932	0.18379	0.23196	0.20196	0.04139	0.19735	0.25462	0.2217
WORST	0.23314	0.03688	0.14928	0.01105	0.15175	0.11802	0.11055	0.01471	0.00009	0.1343	0.22876	0.18748
SD	0.01077	0.06069	0.02339	0.05659	0.0186	0.03786	0.04466	0.04892	0.05281	0.02803	0.01293	0.01501
FR	100	100	100	100	100	100	100	100	100	100	100	100
BEST	0.05676	0.05616	0.05676	0.04887	0.05444	0.05442	0.05676	0.05657	0.00938	0.05511	0.05676	0.05663
MEAN	0.05647	0.01463	0.05142	0.00541	0.02357	0.01743	0.05226	0.03376	0.00064	0.01512	0.05675	0.04892
MEDIAN	0.05676	0.00566	0.0566	0.00003	0.02138	0.0064	0.05666	0.04182	0	0.00735	0.05676	0.0541
WORST	0.04909	0	0.00251	0	0.00013	0.00001	0.00032	0.00007	0	0.00001	0.0567	0.02524
SD	0.0014	0.02005	0.01458	0.0136	0.01737	0.0196	0.01421	0.02205	0.00195	0.01673	0.00001	0.00992
FR	100	100	100	100	100	100	100	100	100	100	100	100

(UNDX), the Simplex crossover (SPX), Parent Centric (PCX), and the triangular crossover (TC), each with a given number of parents and associated constraints. UNDX and SPX use mean-centric probability distribution, whereas

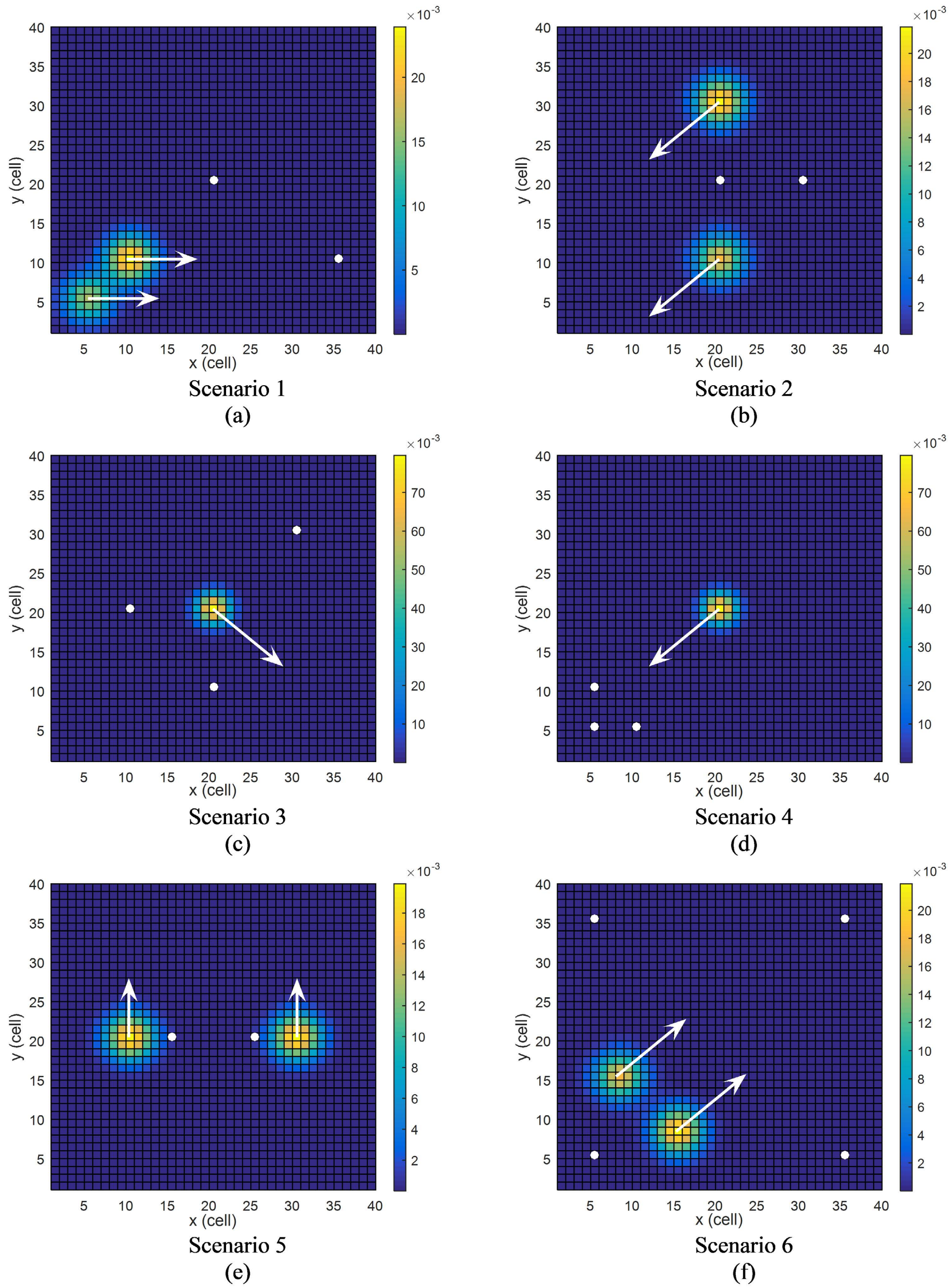

FIGURE 2. Search scenarios.

the PCX is parent-centric. In a GA with multiple parent crossover, the traditional mutation operator is replaced by a randomized operator.

C. MOTION-ENCODED GENETIC ALGORITHM WITH MULTIPLE PARENTS (MEGA-MPC)

Several improvements and modifications to the Genetic Algorithm exist in the literature; the Motion-Encoded Genetic Algorithm with multiple parents in this paper is developed to find a target in motion using multiple UAVs. For the search problem, a global optimum is desired to be reached. This paper proposes using UAV motion to encode the trajectory in a MEGA-MPC algorithm. The UAV motion paths generated evolve over n iterations in the MEGA-MPC. The target search paths represent a set of UAV motion segments, with each track corresponding to the movement of the UAV between adjacent cells. The flowchart of the proposed approach is shown in Figure 1. The process starts with the initialization phase, in which a belief map is created based on the available information. Also, a population of PS individuals is randomly generated in the search space of the problem at hand. Then each individual is coded into a motion-encoded path where

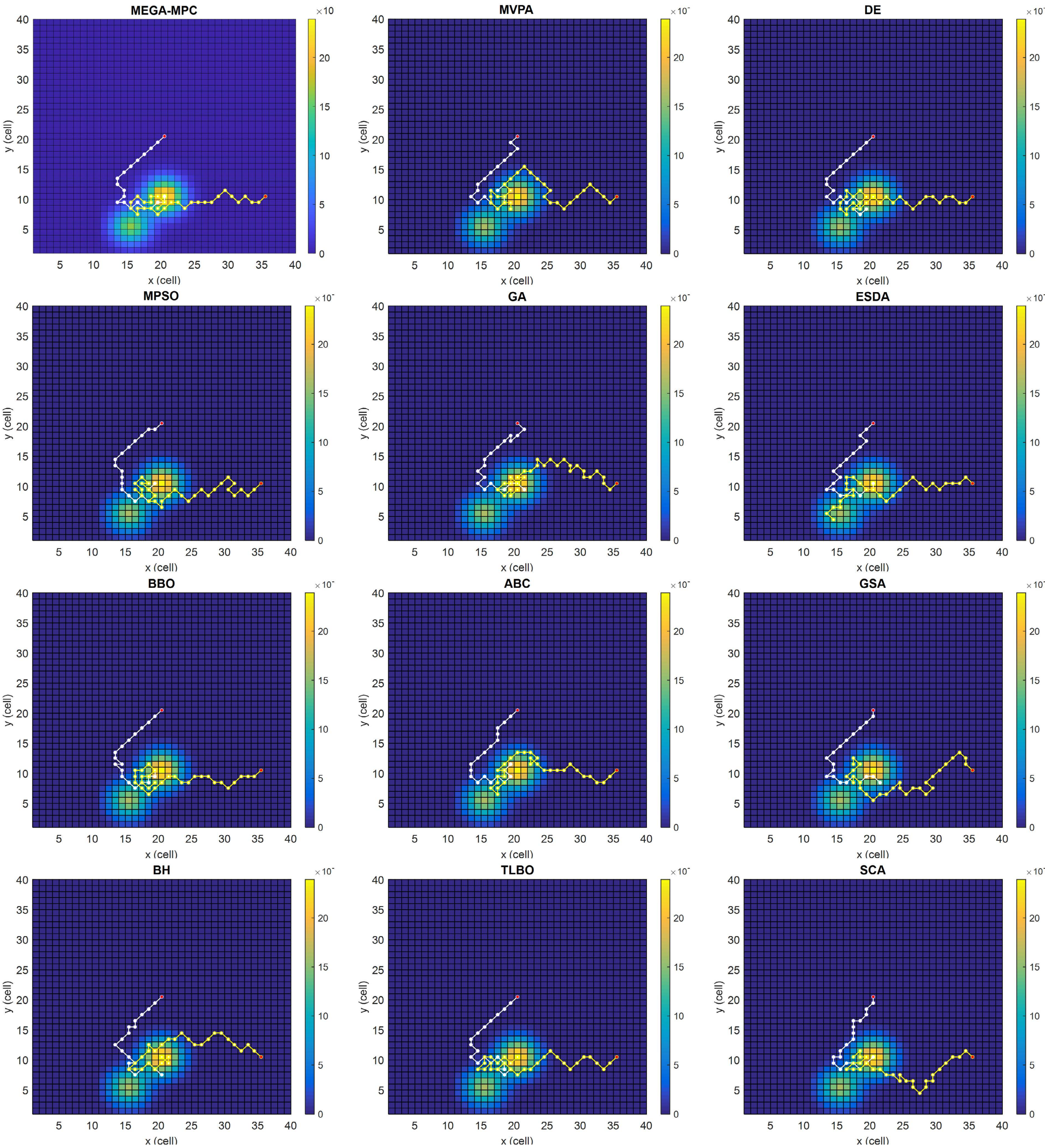

FIGURE 3. **Search paths for scenario 1 obtained using the tested algorithms.**

a search path is then described by a vector of N motion segments, $U_k = (u_{k,1}, u_{k,2}, \cdot u_{k,N})$. and the magnitude and direction of the motion at a particular time t as ψ_t and γ_t, respectively. Once the search path is created for each individual, the objective function is evaluated using the cumulative probability equation given by (14). After that, the population is sorted based on the objective function (cumulative probability), and then the first m paths are saved in the archive pool (A). A section pool with 3PS size is created using a tournament selection procedure with size TC (TC can be randomly selected either 2 or 3). For every three consecutive individuals from the selection pool, three new offsprings are generated using the following expression:

$$\begin{cases} o_1 = x_1 + \beta \times (x_2 - x_3) \\ o_2 = x_2 + \beta \times (x_3 - x_1) \\ o_3 = x_3 + \beta \times (x_1 - x_2) \end{cases}. \tag{15}$$

Then a randomized operator based on a predefined probability changes some of the properties of the generated offsprings using values from the archive pool (A).

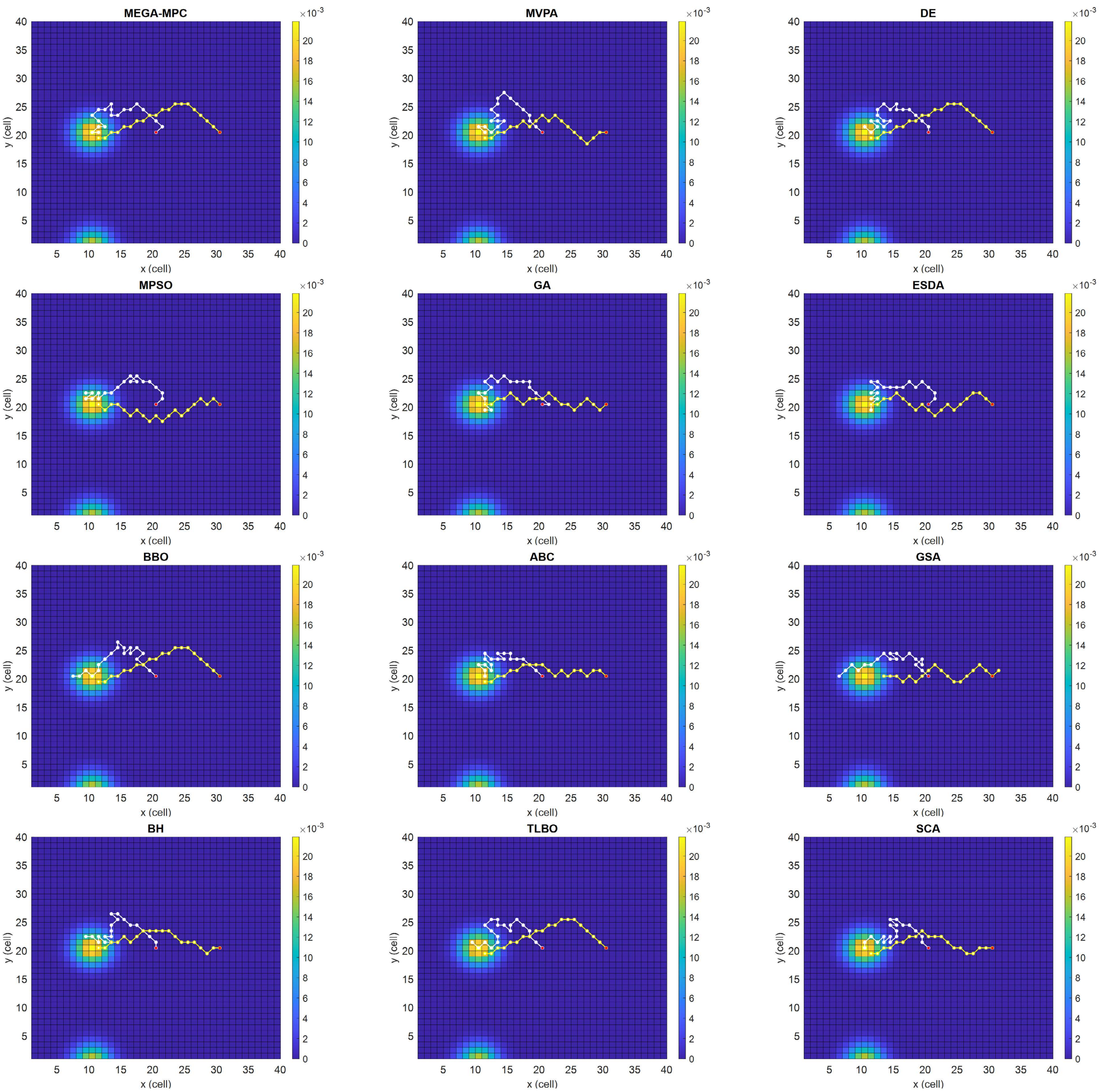

FIGURE 4. Search paths for scenario 2 obtained using the tested algorithms.

Any duplicates in the generated offsprings are removed. Finally, the optimal results are displayed if the termination criterion is met. Otherwise, the solution iterates.

IV. PROPOSED APPROACH FOR DYNAMIC TARGET SEARCH USING MULTI-UAVs

As discussed in the preceding sections of the paper, the Bayesian theory was adopted to formulate finding a moving target or a dynamic target as an optimization problem with the objective function set to maximize target detection probability. In this paper, multi-UAVs are used at the same time. Therefore, to achieve the objectives of the work, the proposed approach for dynamic target search using multi-UAVs is formulated as a parallel optimization problem. Each UAV searches for the target starting from a different location. If there are zones or areas with different probabilities, each UAV tries to find the area with a higher probability. In the case of regions with the same probabilities, the UAVs are divided into groups where the number of groups is equal to the number of areas with different probabilities. For example, if there are 6 areas denoted as area1, area2, area3, area4, area5, and area6 where area1 and area2 have the same probability and area3, area4, area5, and area6 have the same probabilities, then the UAVs are divided into two groups.

The developed MEGA-MPC is implemented to solve parallel optimization problems. In other words, UAVs work in parallel with or without communication between them. Communication between UAVs is mostly needed for areas with the

TABLE 4. Statistical analysis of the outcome of all algorithms for scenario 3.

UAV #	Statistical Analysis	MEGA-MPC	MVPA	DE	PSO	GA	ESDA	BBO	ABC	GSA	BH	TLBO	SCA
UAV # 1	BEST	0.693	0.644	0.687	0.584	0.548	0.642	0.668	0.611	0.511	0.604	0.672	0.630
	MEAN	0.640	0.370	0.622	0.301	0.468	0.476	0.551	0.494	0.229	0.492	0.633	0.562
	MEDIAN	0.649	0.394	0.635	0.314	0.472	0.487	0.594	0.524	0.237	0.509	0.636	0.570
	WORST	0.518	0.014	0.354	0.002	0.362	0.275	0.232	0.269	0.000	0.363	0.560	0.475
	SD	0.039	0.154	0.062	0.173	0.053	0.088	0.106	0.094	0.136	0.075	0.031	0.032
	FR	100	100	100	100	100	100	100	100	100	100	100	100
UAV # 2	BEST	0.779	0.605	0.779	0.421	0.419	0.615	0.746	0.467	0.460	0.474	0.771	0.658
	MEAN	0.658		0.655		0.058	0.264	0.570			0.126	0.676	0.376
	MEDIAN	0.698		0.690		0.008	0.245	0.653			0.019	0.708	0.486
	WORST	0.459		0.410		0.000	0.000	0.001			0.000	0.370	0.000
	SD	0.059		0.101		0.103	0.235	0.186			0.167	0.100	0.221
	FR	100	97	100	67	100	100	100	27	53	100	100	100
UAV # 3	BEST	0.731	0.588	0.714	0.488	0.396	0.609	0.682	0.580	0.325	0.611	0.696	0.536
	MEAN	0.579				0.095	0.189				0.130	0.585	
	MEDIAN	0.640				0.035	0.007				0.027	0.609	
	WORST	0.002				0.000	0.000				0.000	0.000	
	SD	0.140				0.122	0.226				0.183	0.134	
	FR	100	97	97	67	100	100	97	23	40	100	100	93

TABLE 5. Statistical analysis of the outcome of all algorithms for scenario 4.

UAV #	Statistical Analysis	MEGA-MPC	MVPA	DE	PSO	GA	ESDA	BBO	ABC	GSA	BH	TLBO	SCA
UAV # 1	BEST	0.554	0.461	0.554	0.471	0.402	0.514	0.503	0.465	0.335	0.399	0.537	0.441
	MEAN	0.481	0.317	0.455	0.244	0.297	0.312	0.351		0.204	0.288	0.466	0.373
	MEDIAN	0.481	0.327	0.443	0.240	0.297	0.305	0.337		0.205	0.280	0.463	0.366
	WORST	0.420	0.092	0.325	0.050	0.218	0.188	0.226		0.000	0.186	0.373	0.292
	SD	0.035	0.093	0.063	0.082	0.044	0.079	0.076		0.089	0.057	0.040	0.040
	FR	100	100	100	100	100	100	100	93	100	100	100	100
UAV # 2	BEST	0.615	0.526	0.585	0.343	0.479	0.508	0.550	0.486	0.435	0.529	0.585	0.510
	MEAN	0.527	0.310	0.459	0.207	0.353	0.347	0.405	0.330	0.183	0.347	0.528	0.430
	MEDIAN	0.554	0.319	0.475	0.227	0.347	0.352	0.425	0.319	0.200	0.341	0.531	0.432
	WORST	0.408	0.001	0.310	0.000	0.268	0.187	0.246	0.192	0.000	0.196	0.428	0.344
	SD	0.043	0.127	0.080	0.089	0.043	0.084	0.080	0.089	0.119	0.078	0.037	0.047
	FR	100	100	100	100	100	100	100	100	100	100	100	100
UAV # 3	BEST	0.610	0.479	0.610	0.422	0.460	0.506	0.546	0.533	0.419	0.447	0.591	0.539
	MEAN	0.531	0.298	0.490	0.272	0.345	0.335	0.402		0.185	0.338	0.518	0.440
	MEDIAN	0.538	0.305	0.507	0.271	0.342	0.323	0.418		0.201	0.329	0.523	0.450
	WORST	0.471	0.005	0.238	0.043	0.240	0.154	0.253		0.000	0.231	0.392	0.302
	SD	0.035	0.129	0.081	0.105	0.058	0.086	0.091		0.113	0.063	0.051	0.053
	FR	100.0	100.0	100.0	100.0	100.0	100.0	100.0	97.0	100.0	100.0	100.0	100.0

TABLE 6. Statistical analysis of the outcome of all algorithms for scenario 5.

UAV #	Statistical Analysis	MEGA-MPC	MVPA	DE	PSO	GA	ESDA	BBO	ABC	GSA	BH	TLBO	SCA
UAV # 1	BEST	0.262	0.243	0.262	0.236	0.236	0.257	0.258	0.241	0.230	0.239	0.262	0.239
	MEAN	0.255	0.182	0.249	0.146	0.193	0.201	0.229	0.207	0.105	0.201	0.253	0.220
	MEDIAN	0.257	0.195	0.249	0.154	0.190	0.214	0.235	0.210	0.118	0.207	0.253	0.218
	WORST	0.239	0.085	0.215	0.020	0.166	0.108	0.183	0.139	0.011	0.151	0.239	0.193
	SD	0.006	0.046	0.011	0.065	0.015	0.040	0.021	0.025	0.069	0.024	0.007	0.011
	FR	100	100	100	100	100	100	100	100	100	100	100	100
UAV # 2	BEST	0.243	0.228	0.241	0.209	0.205	0.230	0.235	0.227	0.207	0.221	0.243	0.230
	MEAN	0.232	0.171	0.218	0.133	0.172	0.181	0.213	0.191	0.076	0.183	0.233	0.206
	MEDIAN	0.238	0.176	0.233	0.126	0.171	0.187	0.225	0.197	0.080	0.186	0.237	0.205
	WORST	0.153	0.101	0.138	0.014	0.142	0.111	0.136	0.102	0.002	0.130	0.153	0.181
	SD	0.017	0.033	0.036	0.061	0.016	0.036	0.028	0.025	0.053	0.021	0.016	0.012
	FR	100	100	100	100	100	100	100	100	100	100	100	100

same probability to avoid all UAVs searching for the target in the same area.

V. APPLICATION, RESULTS, AND DISCUSSION

A. SCENARIOS

In this work, six scenarios are investigated and simulated. The same grid size ($w_x = w_y = 40$) is used for all scenarios with different number of UAVs, different initial UAV positions, different belief map $b(x_0)$, and different target motion model $P(x_t|x_{t-1})$. Figure 2 depicts the tested scenarios whereby the probability map is color-coded such that warmer colour cells represent higher target probabilities. A white circle indicates UAVs' initial positions, whereas a white arrow depicts the dynamics of the moving targets. These scenarios are: It is

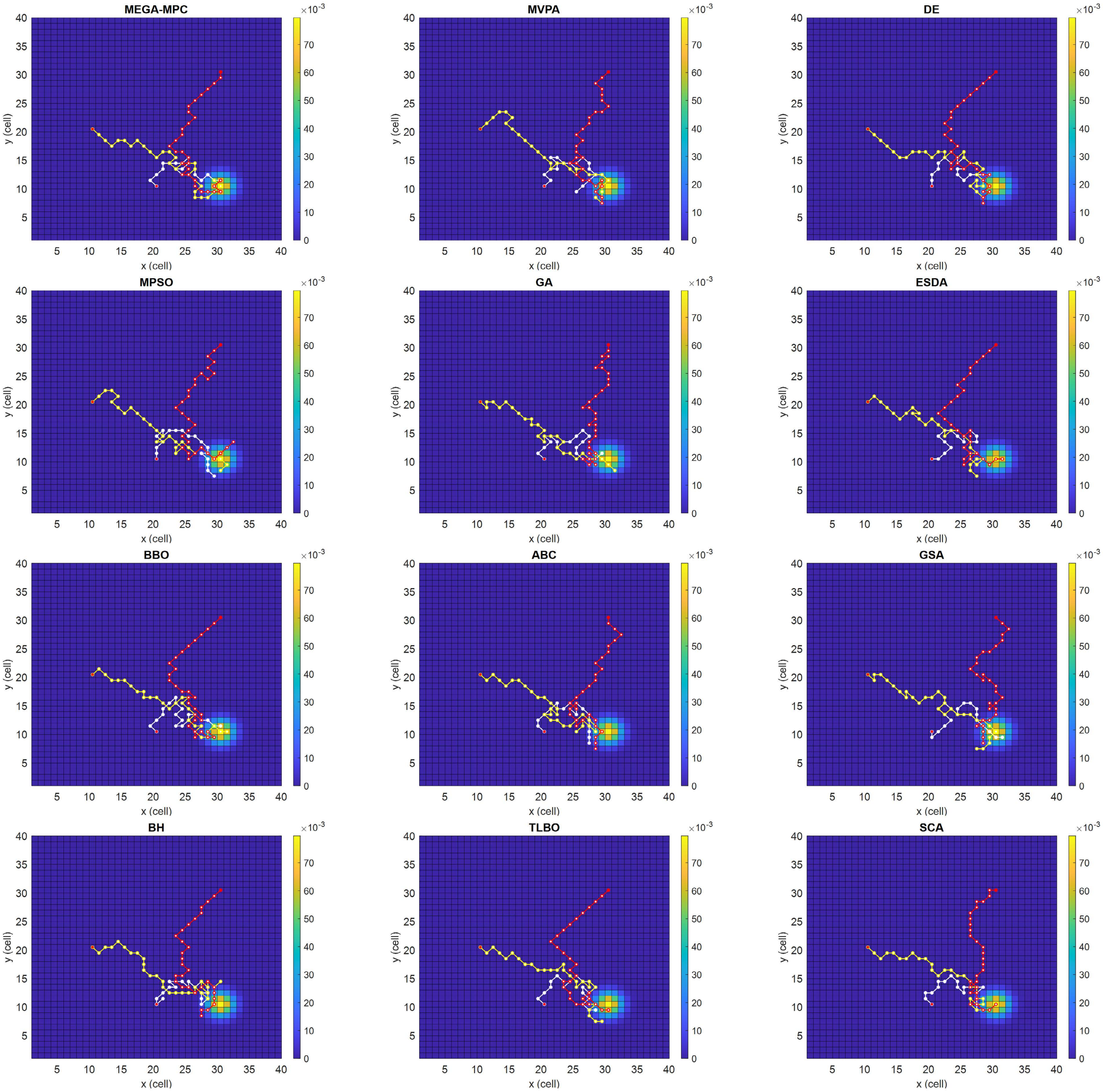

FIGURE 5. Search paths for scenario 3 obtained using the tested algorithms.

worth mentioning here that the present problem, as it is formulated in the paper, can be used to search for both a single or multiple targets using multiple UAVs. Most of the tested scenarios are designed to test one target search using multiple UAVs. However, Scenario 5 is designed to search for multiple targets using multiple UAVs.

- **Scenario 1:** In the first scenario, two areas with high probabilities are located near each other and moving eastwards. The probability of the lower area is slightly lower than that of the upper one. There are two UAVs; the first one is located at the center of the search space, while the second is located to the right of the search space. Figure 2(a) depicts this scenario.
- **Scenario 2:** In the second scenario, the two areas are equally spaced from the center (along the y-axis) of the search region. The probability of the lower area is slightly lower than the upper one. In this case, both areas move toward the southwest. Here also, there are two UAVs with one UAV at the centre of the search space, whilst the other is to the right of the targets and the first UAV, as shown in Figure 2(b).
- **Scenario 3:** The third scenario tests the adaptability of the search algorithm. This scenario is depicted in Figure 2(c), where only one dense area can be seen moving towards the southeast. However, there are three UAVs located around the target in this case.

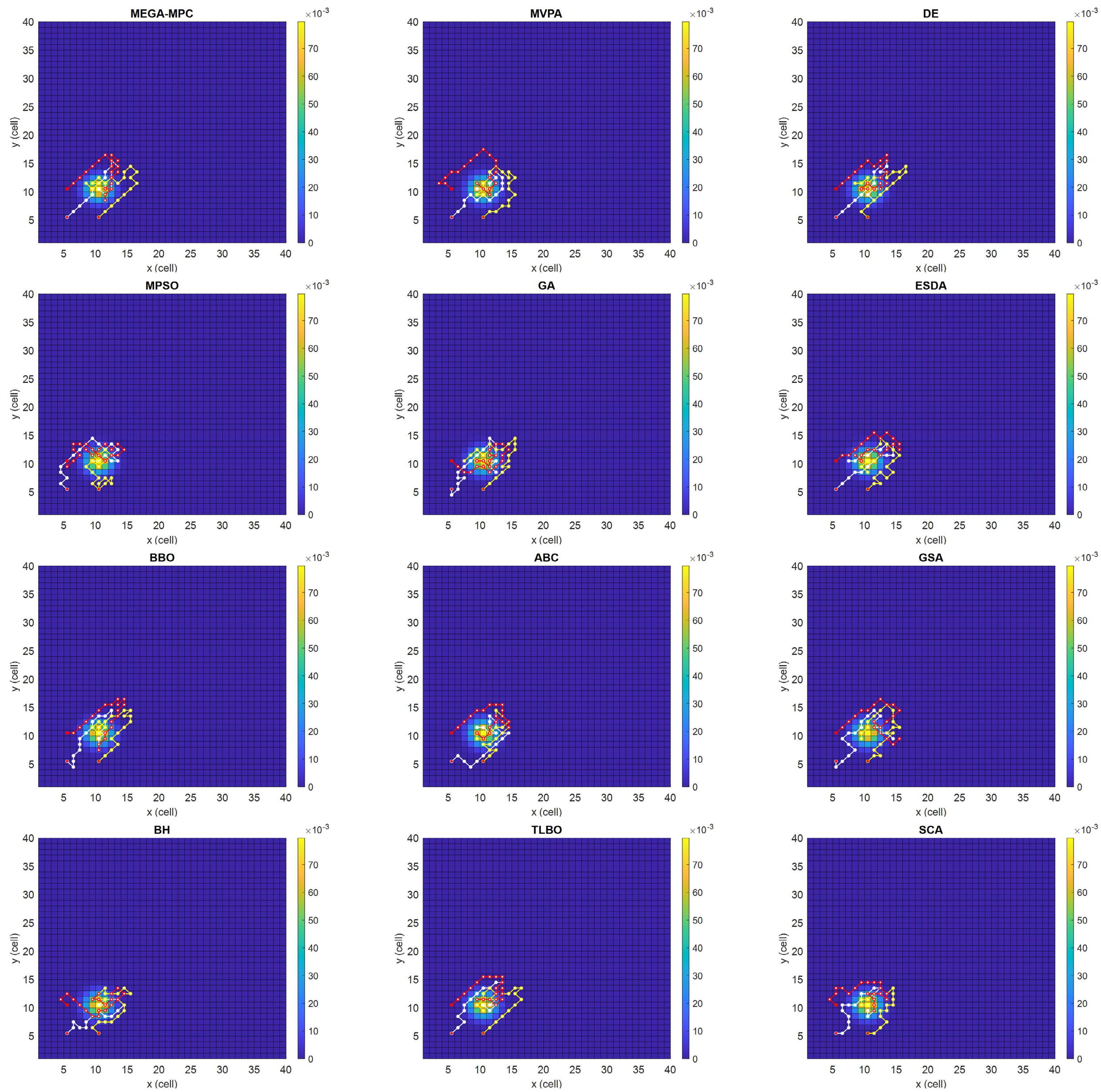

FIGURE 6. Search paths for scenario 4 obtained using the tested algorithms.

- **Scenario 4:** There is only one dense area in this scenario, like the previous one. However, in this scenario, the target moves toward the three UAVs located initially in the southwest of the search space, as shown in Figure 2(d).
- **Scenario 5:** In this scenario, two probability areas are located at the center (along the x-axis) of the search region. Both targets are moving toward the north. There are two UAVs for this scenario near the initial position of the probability area. Since both targets have the same probability, the UAVs are searching for multiple targets here. This scenario is shown in Figure 2(e)
- **Scenario 6:** In this last scenario, depicted by Figure 2(f), there are two probability areas, both located at the lower corner of the search region moving toward the northeast. However, in converse to the previous cases, the probability of the upper area is slightly lower than the lower area. Furthermore, there are four UAVs initially stationed at the four corners of the search region

B. COMPARING ALGORITHMS

In order to compare the proposed algorithm, several well-known algorithms have been selected. The list of algorithms along with their main reference, inspiration source and

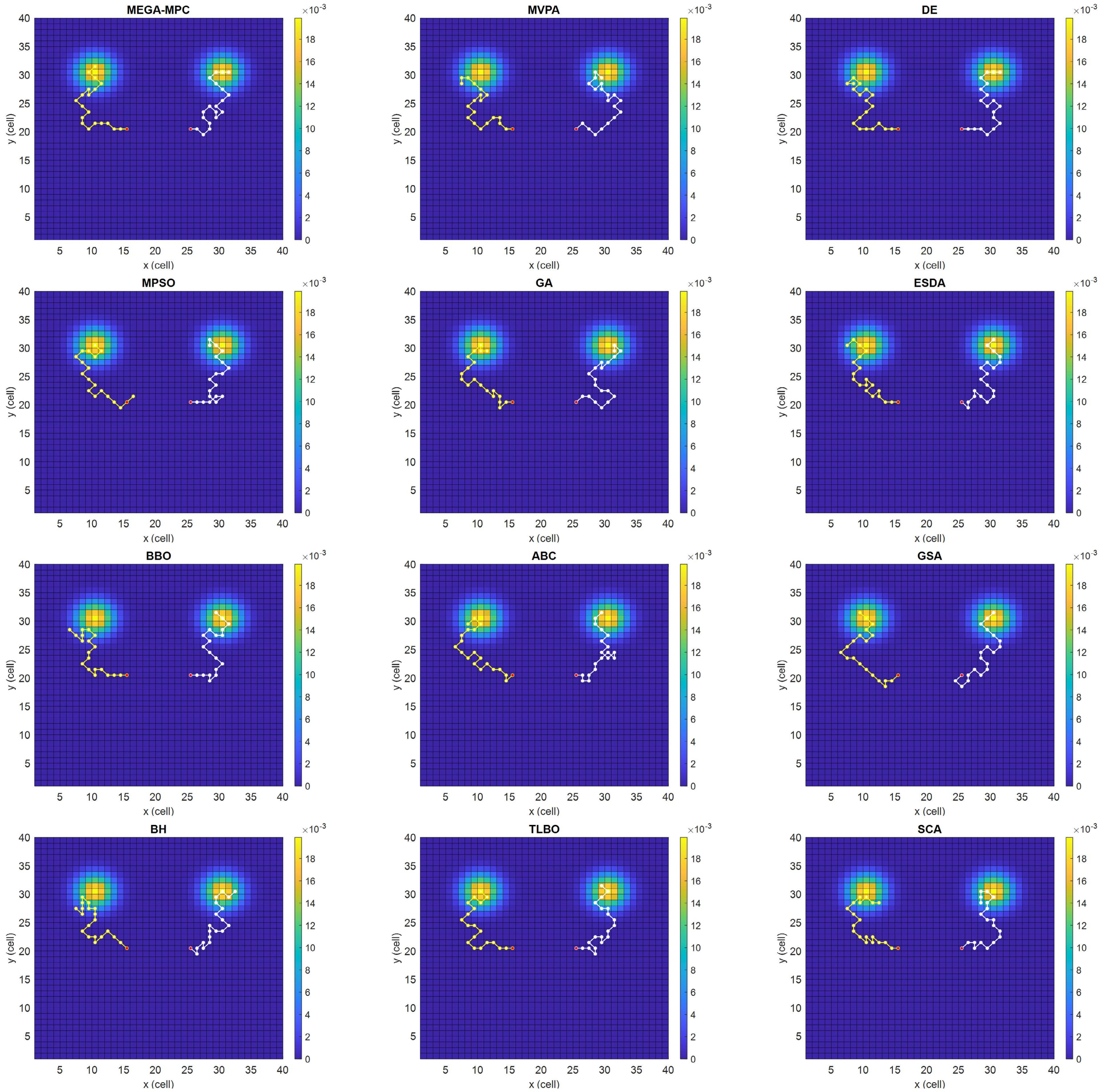

FIGURE 7. Search paths for scenario 5 obtained using the tested algorithms.

control parameters are given in Table 1. In addition to the parameters given in Table 1, the maximum number of iterations for all algorithms is selected as 300. These algorithms have been chosen because the are very competitive and they have been applied in many research works.

C. RESULTS

In the coming section, the obtained results are reported using statistical parameters. The ‘BEST’, the ‘MEAN’, the ‘MEDIAN, the ‘WORST’, the ‘Standard Deviation (SD)’, and the ‘Feasibility Ratio (FR)’ for all the compared algorithms and scenarios are tabulated and discussed. The FR, defined as the ratio of successful runs to total attempted runs, indicates how successful the considered algorithm is.

1) SCENARIO 1

We recall that in this scenario, there are two UAVs, the first one located at the centre of the search space whilst the second one is towards its right side. The results for scenario 1 are tabulated in Table 2. The following observations are apparent from the obtained results:

- For the first UAV, the proposed MEGA-MPC obtained the best results for all the statistical parameters, and the FR is 100%. For the second UAV, the proposed algorithm had the best results for all the comparing

TABLE 7. Statistical analysis of the outcome of all algorithms for scenario 6.

UAV #	Statistical Analysis	MEGA-MPC	MVPA	DE	PSO	GA	ESDA	BBO	ABC	GSA	BH	TLBO	SCA
UAV # 1	BEST	0.307	0.267	0.301	0.168	0.143	0.263	0.292	0.201	0.216	0.187	0.293	0.233
	MEAN	0.273										0.252	
	MEDIAN	0.285										0.265	
	WORST	0.170										0.001	
	SD	0.035										0.058	
	FR	100	60	97	30	97	97	87	17	27	93	100	70
UAV # 2	BEST	0.259	0.223	0.245	0.143	0.135	0.198	0.241	0.147	0.027	0.204	0.255	0.185
	MEAN	0.187				0.054						0.210	
	MEDIAN	0.208				0.047						0.216	
	WORST	0.000				0.000						0.160	
	SD	0.048				0.042						0.026	
	FR	100	77	80	30	100	83	80	13	23	90	100	73
UAV # 3	BEST	0.190	0.152	0.183	0.108	0.070	0.130	0.187	0.081	0.098	0.108	0.181	0.110
	MEAN	0.108				0.013							
	MEDIAN	0.125				0.003							
	WORST	0.000				0.000							
	SD	0.059				0.021							
	FR	100	70	73	40	100	93	77	10	13	97	97	77
UAV # 4	BEST	0.220	0.173	0.214	0.113	0.096	0.179	0.207	0.157	0.133	0.158	0.219	0.155
	MEAN	0.164				0.043						0.186	
	MEDIAN	0.182				0.045						0.187	
	WORST	0.001				0.000						0.113	
	SD	0.045				0.031						0.027	
	FR	100	67	93	33	100	93	87	13	17	93	100	63

statistical parameters except for the SD, and it also obtained 100 as FR.

- For the first UAV, all the algorithms have an FR of 100%. In other words, all the algorithms could find a feasible path in all runs. However, for the second UAV, only three algorithms achieved an FR of 100%.

Furthermore, Figure 3 shows the optimal search paths for each UAV for all tested algorithms. It is worth mentioning that the sketched path represents the search path in this figure (and in the similar figure for the remaining scenarios). However, the presented belief map depicts the target's final step. The targets' evolution can be visualised by comparing this map with the one illustrated in Figure 2 to observe target evolution. Figure 3 shows that the proposed MEGA-MPC algorithm allowed the two UAVs to track the targets, thereby finding the highest probability region.

2) SCENARIO 2

This scenario had two UAVs, one at the centre of the search space and the other at a midpoint along the y-axis, to the right of the targets and the first UAV along the x-axis. The results obtained for scenario 2 are tabulated in Table 3. The following observations are made from it:

- For the first UAV, MEGA-MPC has achieved the best results for all the considered statistical parameters, and the FR is 100%. For the second UAV, the proposed algorithm obtained the best results for the 'BEST' and the 'MEDIAN' statistical parameters, whilst the TLBO has obtained the best results for the remaining statistical parameters. It has obtained 100 as FR.
- For both UAVs, all the algorithms have an FR of 100% the runs.

Figure 4 shows the optimal search paths for each UAV for all tested algorithms. The figure shows that the MEGA-MPC algorithm allowed the two UAVs found the highest probability region by following the target paths.

3) SCENARIO 3

We recall that in this scenario, there are three UAVs located around the target, represented by a dense area. The results for scenario 3 are tabulated in Table 4. The following comments can be made from this table:

- For the first UAV, the proposed MEGA-MPC obtained the best results in terms of the statistical parameters; 'BEST', 'MEAN', and 'MEDIAN'. TLBO, on the other hand, had the best results for the 'WORST' and the 'SD' statistical parameters.
- For the second UAV, MEGA-MPC had the best results for the 'BEST', 'WORST' and 'SD' statistical parameters, whilst the TLBO obtained the best results for the remaining statistical parameters, and it got an FR of 100%.
- For the third UAV, the proposed algorithm obtained the best results in all the compared statistical parameters except for the 'MEAN' value, where the best result is obtained using the TLBO algorithm.
- For the first UAV, all the algorithms have an FR of 100%. For the second UAV, only 66% of the algorithms have obtained an FR of 100%. Finally, for the third UAV, only 42% of the algorithms obtained an FR of 100%. For the

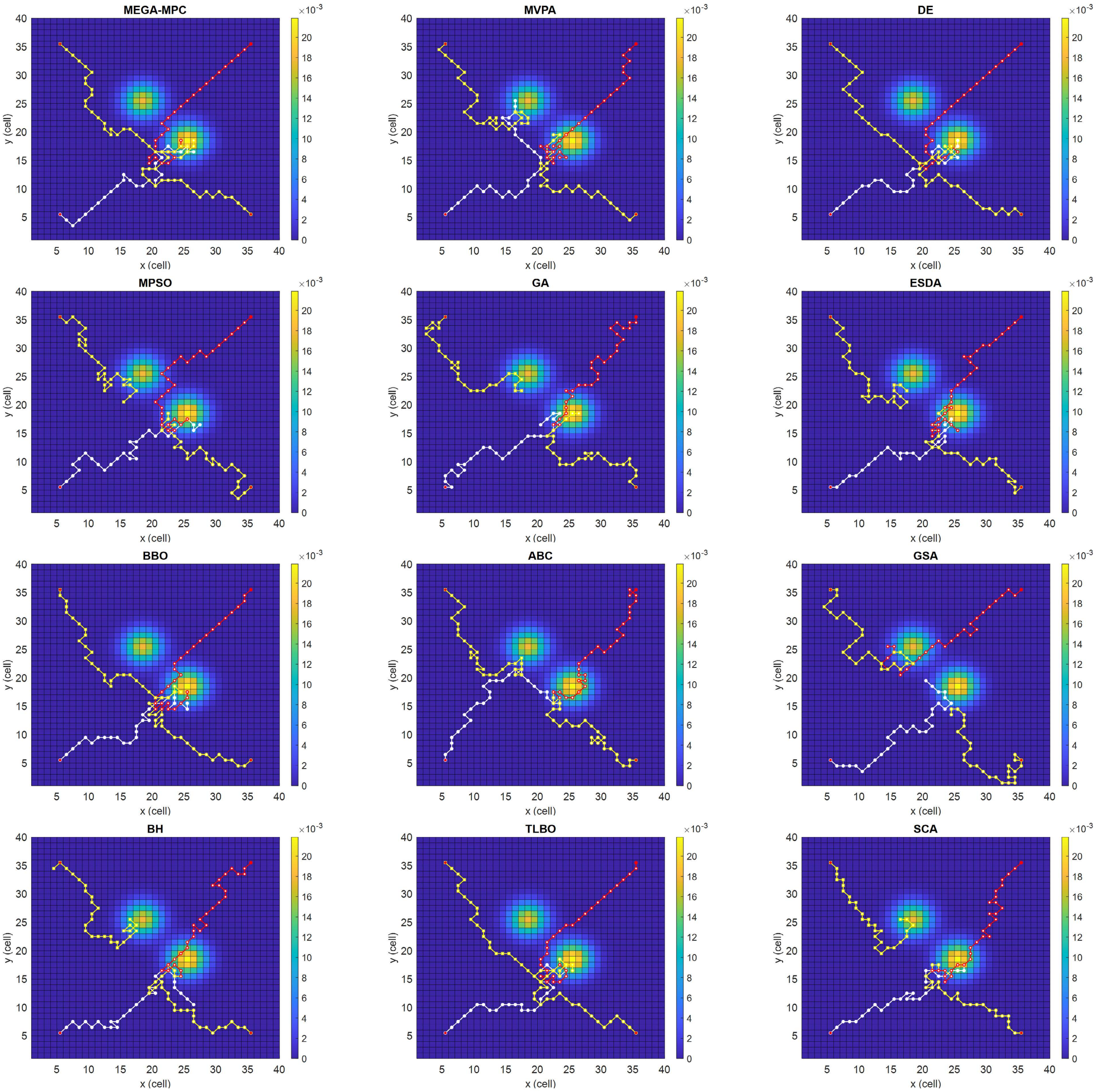

FIGURE 8. Search paths for scenario 6 obtained using the tested algorithms.

three UAVs, the proposed algorithm has obtained an FR of 100%.

Figure 5 shows the optimal search paths for each UAV for all tested algorithms. It can be seen from Figure 5 that the MEGA-MPC algorithm allowed the three UAVs to find the targets by following their tracks.

4) SCENARIO 4

Recall that there is only a single dense area in this scenario, with the target moving toward the three UAVs initially located in the southwest region of the search space. The results for this scenario are tabulated in Table 5. For this scenario, we observe the following from the table:

- For the first UAV, MEGA-MPC had the best 'MEAN', 'MEDIAN', and 'SD' while the DE had obtained the best results in terms of the 'BEST' value.
- For the second UAV, MEGA-MPC obtained the best results for the 'BEST' and the 'MEDIAN' while the TLBO had the best results for the remaining statistical parameters, and it has an FR of 100%.
- For the third UAV, the proposed algorithm obtained the best results in all the compared statistical parameters.
- For the first and third UAVs, all the algorithms have an FR of 100% except for the ABC. For the second UAV, all the algorithms have obtained an FR of 100%.

The optimal search paths for all UAVS and algorithms are shown in Figure 6. It is seen that the proposed algorithm allowed the three UAVs to find the target, represented by the dense area, by following the target paths.

5) SCENARIO 5

In this scenario, there are two probability areas located at the centre of the search region along the x-axis. Both targets are moving toward the north. There are two UAVs situated near the probability area's initial position for this scenario. The results for scenario 5 are tabulated in Table 6. The following observations can be made from the results:

- For the first UAV, MEGA-MPC had the best results in all the compared statistical parameters.
- For the second UAV, MEGA-MPC had the best results for the 'BEST' and 'MEDIAN'. TLBO got the best 'MEAN', and SCA obtained the best values for 'WORST' and 'SD'.
- For both UAVs, all the algorithms converged in all runs (i.e., FR = 100%).

Figure 7 shows the optimal search paths found for each UAV. The results show that the proposed algorithm allowed each UAV to follow the target paths. With the aid of communication between UAVs, each of the two UAVs found one of the two areas with the same probability.

6) SCENARIO 6

In scenario 6, the two probability areas are located at the search region's lower corner, moving toward the northeast. The upper area had a slightly lower probability than the lower one. The four UAVs were initially positioned at the four corners of the search region. The results for this scenario are shown in Table 7. The following can be deducted from the presented results:

- For the first UAV, the proposed MEGA-MPC obtained the best results in all the compared statistical parameters.
- For the second UAV, MEGA-MPC obtained the best results for the 'BEST' value while TLBO had the best results for the remaining parameters.
- For the third UAV, the proposed algorithm also obtained the best results in all the compared statistical parameters except the 'SD' value.
- For the fourth UAV, the proposed algorithm obtained the best 'BEST' value while TLBO got the best values for the remaining statistical parameters.
- For the first UAVs, only the MEGA-MPC and the TLBO obtained an FR of 100%. Only three algorithms converged in all runs for the remaining three UAVs, with an FR of 100%. Therefore, this scenario is the most difficult to tackle among the six scenarios investigated.

Figure 8 shows the optimal search paths found for each UAV. Figure 8 shows that the proposed algorithm allowed each UAV to follow the target paths. Since there are two areas with the same probabilities, each UAV followed one target and was able to find it.

D. DISCUSSION

The obtained results in this study demonstrate the superiority of MEGA-MPC over the well-known and widely used algorithms considered in this paper. The observed success of the MEGA-MPC can be attributed to the search capability of the ECPO and the motion-encoded mechanism introduced to the ECPO. We believe that these two features, exploited to develop the MEGA-MPC algorithm, have immensely contributed to its excellent performance. First, ECPO is a robust and reliable algorithm as it is ranked among the top 5 algorithms, even without the ME mechanism. Secondly, implementing an ME mechanism with the ECPO enhanced performance in locating moving targets using a single UAV. This mechanism aided ECPO in avoiding the creation of non-valid search paths while searching. Finally, the ME mechanism's transformation from the cartesian to the motion space assisted in adapting ECPO-ME to incorporate the dynamics of the moving target.

VI. CONCLUSION

This paper uses a novel approach based on a variant of the famous genetic algorithm using multiple (GA-MPC) and a Motion-Encoded mechanism to search for dynamic targets using multiple UAVs. The target search problem was converted from a cartesian problem to a motion-based one via space transformation using the motion encoding feature. This transformation allowed the search path to be represented by a series of motions in which UAVs move to neighboring cells from their present location. Different numbers of UAVs were used to test the developed algorithm on six unique scenarios with varying complexities. The algorithm's performance was evaluated by comparing it with eleven reputable metaheuristics. The analysis of the results demonstrated the effectiveness and reliability of the proposed algorithm applied to dynamic-targets search with multiple UAVs.

In this paper, only the cumulative probability was considered in the objective. Other objectives like fuel consumption or avoidance of forbidden areas and obstacles and other constraints can be considered for further work. These considerations would make the problem a multi-objective one, constituting future extensions.

Furthermore. it is worth to mention that in this paper the approach was to formulate the problem of finding targets as an optimization problem and then it has been solved using an efficient optimization algorithm. However, there are other approaches to investigate in the future based on Deep Learning (DL) as it has been explored in [48].

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