3D Optimal Surveillance Trajectory Planning for Multiple UAVs by Using Particle Swarm Optimization With Surveillance Area Priority

HU TENG, ISHTIAQ AHMAD, ALAMGIR MSM, AND KYUNGHI CHANG, (Senior Member, IEEE)
Department of Electronic Engineering, Inha University, Incheon 22212, South Korea
Corresponding author: Kyunghi Chang (khchang@inha.ac.kr)

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea Government (MSIT) under Grant NRF-2019R1F1A1061696.

ABSTRACT The use of the unmanned aerial vehicle (UAV) has been regarded as a promising technique in both military and civilian applications. However, due to the lack of relevant laws and regulations, the misuse of illegal drones poses a serious threat to social security. In this paper, we develop a trajectory planner based on particle swarm optimization and a proposed surveillance area importance updating mechanism aimed at deriving three-dimensional (3D) optimal surveillance trajectories for multiple monitoring drones. We also propose a multi-objective fitness function in accordance with energy consumption, flight risk, and surveillance area priority in order to evaluate the trajectories generated by the proposed trajectory planner. Simulation results show that the trajectories generated by the proposed trajectory planner can preferentially visit important areas while obtaining a high fitness value in various practical situations.

INDEX TERMS Particle swarm optimization, 3D path planning, surveillance area priority, multiple unmanned aerial vehicles.

I. INTRODUCTION
Unmanned aerial vehicles (UAVs), also known as drones, have become increasingly important in both military and civilian applications over the past few decades in areas such as remote sensing [1], sensor data collection [2], [3], UAV-enabled communications [4], [5], relays for ad hoc networks [6], disaster monitoring [7], flood area surveillance [8], and wildfire tracking [9]. However, due to a lack of proper laws and regulations, the misuse of drones poses a serious threat to public safety. Since monitoring drones (MDrs) are usually powered by a battery, feasible surveillance trajectories for MDrs should be carefully designed considering their physical restrictions. As a fundamental element of an UAV autonomous control module, the UAV trajectory planning problem has been studied for decades. It can be formulated as an optimization problem that finds the feasible path from the source to the destination. And the optimal trajectory is usually associated with the path that maximizes (or minimizes) a certain optimization index (e.g., energy consumption, path length, etc.) of a certain mission.

A. RELATED WORK
To derive the optimal trajectory, many researchers have proposed numerous trajectory planners. Turker et al. proposed a path planner based on a simulated annealing algorithm to obtain a nearly optimal path in a two-dimensional (2D) radar-constrained environment [10]. In [11], Yoo et al. utilized the A* algorithm to derive the optimal UAV trajectory to collect sensing data in a wireless sensor network. However, those proposals (designed for a 2D environment) failed to be applied in 3D operational space, since more constraints need to be modeled to acquire the optimal trajectories. For 3D trajectory planning, algorithms like D* [12], rapidly exploring random tree (RRT) [13], bio-inspired algorithms [14], [15], or an evolutionary algorithm (EA) [16]–[19] are used.
Since finding the optimal solution to the trajectory problem is non-deterministic polynomial time-complete [20], EAs are the best optimizers due to their advantages when dealing with highly complicated 3D trajectory planning problems. In [18], a state-of-the-art variant of a differential evolutionary (DE) algorithm was employed to solve the 3D trajectory planning problem in a snared environment. For multiple UAV path planning, Besada-Portas et al. [17] proposed a trajectory planner based on a multiple coordinated agents coevolution EA (MCACEA), in which the optimization criteria include 11 optimization indexes and constraints. Li et al. [21] proposed a variable neighborhood descend (VND) enhanced genetic particle swarm optimization (PSO) trajectory planner for multiple UAVs in an agricultural application scenario. However, the operational time and the path length are the only optimization indexes in their scheme. Differences in system methodologies in the literature results in difficult to compare the proposed strategy with the other researches.

In the literature, there are several techniques based on acoustic data for feature extraction, such as harmonic line association [22], [23], the wavelet transform [24], and the mel-frequency cepstral coefficient (MFCC) [25] method. The second step is classification, and for this, many mathematical models can be used, such as the support vector machine (SVM) [26], the Gaussian mixture model [27], and the hidden Markov model (HMM) [28]. Kaleem and Rehmani presented schemes for drone localization and tracking [29]. Therefore, it is very difficult to compare the proposed acoustic-based scheme for positioning and tracking of illegal drones strategy with the other researches. Hence, different philosophy and targets of system designs in [10]–[29] result in totally different system parameters. For comparative performance analysis, we are unable to compare our approach with the existing literature because there is no work is available in the literature like ours scenario. Hence, it is not suitable to compare the performances due to different system methodologies. Unlike the resource-allocation and interference-mitigation schemes [30]–[46], this paper addresses three dimension optimal surveillance trajectory planning for multiple UAVs by using PSO with surveillance area priority.

**B. MAIN CONTRIBUTIONS**

The objective of this paper is to derive the optimal surveillance trajectories for multiple monitoring drones to surveil a certain operational area, and to detect the existence of illegal drones (IDrs). To solve this problem, we propose a trajectory planner based on PSO and surveillance area priority. Moreover, we extend our trajectory planner to a 3D environment. Using the proposed trajectory planner, the optimal trajectories can be obtained from all possible trajectories in accordance with the proposed fitness function. In our proposed multi-objective fitness function, not only the energy consumption (EC) but the UAV maneuverability, flight risk, and surveillance area priority are also jointly considered cost-determinant. Taking into consideration all these aspects make our approach more practical in UAV trajectory planning.

The rest of the paper is organized as follows. Section II presents the problem description n, along with explanations of terrain and trajectory representation. A multi-objective fitness function for trajectory optimization is introduced in Section III. Then, the proposed surveillance area priority updating mechanism is presented in Section IV, and the trajectory planner is described in Section V. In Section VI, the simulation results and performance analysis of the proposed trajectory planner are illustrated in detail. Finally, we provide concluding remarks in Section VII.

**II. SYSTEM MODEL AND PROBLEM FORMULATION**

**A. PROBLEM DESCRIPTION**

As shown in Figure 1, MDrs with similar specifications are employed to surveil the whole operational area to detect the existence of IDrs in 3D operational space. During the surveillance, we stipulate that the MDrs cannot enter any area where prohibited by regulations. To avoid being destroyed as a hostile drone, the MDr also cannot approach the ground-based detection system (GBDS) areas equipped for ground-based drone detection. Furthermore, we assume the MDrs communicate with each other by UAV-to-ground link or in an ad-hoc manner. Therefore, MDrs can mutually share information during execution of the flight task.

In our implementation, we discretize the whole operational area into several small unit areas called cells, as shown in Figure 2, in which the area in red represents the restricted area. We assume that an MDr can cover four cells from a certain position (i.e., a waypoint) depending on the coverage slope of the camera imaging sensor on board (i.e., the areas marked in blue).

**B. TERRAIN REPRESENTATION**

To mimic a real-life terrain, we adopt a variant of the Foxhole Shekel function (Figure 3) in our paper to represent the landscape, which is formulated as expressed in [47] (1):

\[ F(X) = \sum_{i=1}^{10} \frac{0.1}{\sum_{j=1}^{10} (x_j - \eta_j)^2 + \gamma_i} \]

where parameters \( \eta \) and \( \gamma \) are utilized to vary the terrain shape. Due to the lack of widely accepted benchmarks in the field of trajectory planning for UAVs, we adopted this terrain because the local maxima of the landscape can be considered mountains.

**C. TRAJECTORY REPRESENTATION**

In our implementation, the trajectories generated by the optimization algorithm are a sequence of three-dimensional waypoints. Therefore, a feasible path is encoded as a vector where the element \( w_i = (x_i, y_i, z_i) \) represents the \( i \)-th waypoint, as shown in (2):

\[ Trajectory = (w_1, w_2, \ldots, w_{N_w}) \]

where \( N_w \) is the number of waypoints in a feasible trajectory.
III. FITNESS FUNCTION FOR UAV TRAJECTORY OPTIMIZATION

In this section, to evaluate the trajectories generated by the proposed multi-UAV path-planning algorithm, we propose a multi-objective fitness function that consists of eight optimization indexes. To emphasize the importance of different optimization indexes during the optimization process, we divide them into two groups and assign different priority levels: (I) the constraints (terrain, forbidden areas, turning angle, flying slope, and multi-UAV collision avoidance) that the UAV must satisfy due to its physical limitations, and (II) the optimization objectives (energy consumption, flying risk, and surveillance area importance) that must be maximized according to certain mission criteria.

Table 1 shows these classifications and the equations to calculate them. For all possible UAV trajectories, the one with the higher fitness value is always preferred. Therefore, we formulate the fitness function as:

\[ F_{fitness} = F_{objective} + TC + FAC + TAC + FSC \]  

(3)

where \( F_{objective} \) is the objective function for which we need to maximize the value in order to derive an optimal trajectory. The rest of the parts correspond to the constraints that should be satisfied before planning a trajectory. More details will be explained in the following sections.

A. OBJECTIVE FUNCTION DESIGNING

One of the optimization criteria is the objective function, which is used to improve the quality of trajectory planning. We define the objective function as a weighted component of energy consumption, flight risk, and surveillance area importance. So, the objective function is formulated as expressed in (4):

\[ F_{objective} = -w_1 F_{EC} - w_2 F_{FR} + w_3 F_{SAI} \]  

(4)

where \( F_{EC}, F_{FR}, \) and \( F_{SAI} \) are defined in the range \([0, 1]\), and \( w_i(i = 1, 2, 3) \) is the weight of each component, which
reflects the important differences while evaluating a candidate path. Intuitively, a path with less energy and flight risk, but a higher surveillance area importance value, is always preferable. So, we stipulate energy consumption and flight risk as negative values, whereas surveillance area importance is positive.

1) ENERGY CONSUMPTION
Small drones are usually powered by a battery, which means they must finish the surveillance task before consuming all their energy. Thus, a feasible path with lower fuel consumption is always preferred. We assume the UAV velocity is constant during the operational time. The EC can be formulated as follows:

\[ F_{EC} = \sum_{i=1}^{N_w-1} \frac{EC_i}{\max EC} \]

where \( EC_i \) is the fuel consumption from the \( i \)th waypoint to the \( (i + 1) \)th waypoint. \( P_u \) is the energy consumption at velocity \( v \) for the time unit; \( t_{i,i+1} \) is the flight time from the \( i \)th waypoint to the waypoint \( (i + 1) \); \( d_{i,i+1} \) is the 3D flight cartesian distance between the \( i \)th waypoint and \( (i + 1) \); and \( \max EC \) is the normalized constant value, formulated as:

\[ \max EC = (N_w - 1) \times P_u \times \frac{d_{\max}}{v}, \quad d_{\max} = \sqrt{X^2 + Y^2 + Z^2} \]

where the X, Y, and Z representing the x-axis, y-axis, and z-axis, respectively.

2) FLYING RISK
The physical characteristics (e.g., small and lightweight) of the MDr make it susceptible to weather conditions (e.g., rain, snow) during the surveillance task. In addition, flying altitude can be another big risk, since a higher altitude means stronger winds in which the MDr s may be accidentally destroyed. Based on the above scenario, we define the following two kinds of flight risk (FR).

\( a: \) ENVIRONMENTAL RISK

Due to the strong random characteristics of environmental risk, it is difficult to build a precise mathematical model. For simplicity, we randomly generated an environmental risk value for each waypoint. And the environmental risk, \( r_{i,i+1}^{e} \), between the \( i \)th waypoint and waypoint \( (i + 1) \) is defined as the sum of their environmental values.

\( b: \) FLYING ALTITUDE RISK

The flying altitude risk is proportional to the absolute flying altitude difference between each of two waypoints. Therefore, we formulate flying altitude risk \( r_{i,i+1}^{a} \) as expressed in (10):

\[ r_{i,i+1}^{a} = \chi \times (z_{i+1} - z_i) \]

where \( \chi \) is a constant control parameter.

Flying risk is a location-dependent parameter, and it increases or decreases only depending on the weather conditions and UAV flying altitude during the flight. The total flying risk can be computed as seen in equations (11) to (13):

\[ F_{FR} = \sum_{i=1}^{N_w-1} \frac{FR_i}{\max FR} \]

\[ FR_i = w_{ER}r_{i,i+1}^{e} + w_{AR}r_{i,i+1}^{a}, \quad w_{ER} + w_{AR} = 1 \]

where \( FR_i \) is the flight risk from the \( i \)th waypoint to the waypoint \( (i + 1) \), and \( w_{ER} \) and \( w_{AR} \) are the weights of the environmental risk and the flight altitude risk, respectively; \( \max FR \) is the normalized constant value, which is written as:

\[ \max FR = (N_w - 1) \times [w_{AR} \times Z + w_{ER} \times (2 \times \max r^e)] \]

where \( \max r^e \) represents the maximum environmental risk and Z represents the flying altitude.

---

**TABLE 1. Classifications for optimization indexes.**

| I. Constraints | Terrain | Forbidden Area | Turning Angle | Flying Slope | Collision Avoidance |
|----------------|---------|----------------|---------------|--------------|---------------------|
| Abbreviation   | TC      | FAC            | TAC           | FSC          | CAC                 |
| Equation       | (17)    | (18)           | (19-20)       | (21-22)      | (23)                |
| Priority level | 1st     | 1st            | 1st           | 1st          | 1st                 |
| Value/Range    | 0       | 0              | 0             | 0            | 0                   |

| II. Optimization Objectives | Energy Consumption | Flight Risk | Surveillance Area Importance |
|-----------------------------|-------------------|-------------|-----------------------------|
| Abbreviation                | EC                | FR          | SA1                         |
| Equation                    | (5-9)             | (10-13)     | (14-16)                     |
| Priority level              | 2nd               | 2nd         | 2nd                         |
| Value/Range                 | [0,1]             | [0,1]       | [0,1]                       |
3) SURVEILLANCE AREA IMPORTANCE
When an MDr is assigned to execute a certain surveillance task, we want it to first surveil important areas, i.e., to obtain higher surveillance area importance (SAI) values. Thus, we introduce SAI values to characterize different surveillance area priorities among the cells. In our implementation, we assign a random SAI value to each cell, which applies to the whole grid on the map. The random assignment of SAI values means that some cells have higher SAI values while the others have lower SAI values. So, the normalized SAI value of a feasible trajectory can be calculated by equations (14) to (16):

\[
F_{SAI} = \frac{\sum_{i=1}^{N_w} SAI_i(t)}{\text{max} SAI} \quad (14)
\]

\[
SAI_i = \sum_{cell \in N(i)} v_{cell} \cdot N(i) \quad (15)
\]

\[
\text{max} SAI = N_w \times N_n \times V_{\text{max}} \quad (16)
\]

where \(SAI_i(t)\) and \(v_{cell} \cdot N(i)\) are the SAI values of the \(i\)-th waypoint and of cell \(x\) for flight time \(t\), respectively. \(N(i)\) is the cell set supervised from the \(i\)-th waypoint. \(N_w\) is the number from \(N(i)\), and \(V_{\text{max}}\) is the maximum SAI value.

B. CONSTRAINT FUNCTION DESIGN
The constraint functions are used to evaluate the feasibility of a path. When they are satisfied, each constraint is equal to 0, but a negative penalty value, \(Q\), is chosen when they are not. By choosing a value for \(Q\) that is less than -1, we can guarantee that the fitness values of feasible paths are always greater than any unfeasible ones. Therefore, we can always obtain a feasible trajectory if all constraint functions are satisfied during the optimization process.

1) TERRAIN CONSTRAINT
An MDr cannot literally go through the terrain (e.g., collide with mountains). Thus, the flying altitude of an MDr must be higher than the terrain’s altitude. We use terrain function \(Altd(x, y)\), explained in Section III, to determine the altitude of any position \((x, y)\). Then the terrain constraint can be described as:

\[
TC = 0, \quad TC = \sum_{i=1}^{N_w} TC_i
\]

where \(TC_i = \begin{cases} Q, & \text{if } z_j < Altd(x_i, y_i) \\ 0, & \text{otherwise} \end{cases} \quad (17)
\]

2) FORBIDDEN AREA CONSTRAINT
For some specific areas (e.g., sensitive government regions), the MDr cannot enter due to regulations. A legal path should be carefully designed to avoid those restricted areas. For the sake of simplicity, we assume that those forbidden areas are rectangles. The forbidden area constraint (FAC) can be formulated as:

\[
FAC = 0, \quad FAC = \sum_{i=1}^{N_w} FAC_i
\]

where \(FAC_i = \begin{cases} Q, & \text{if } \text{waypoint } i \text{ in } \text{Range}(x_j, y_j) \\ 0, & \text{otherwise} \end{cases}
\]

\[
\text{Range}(x_j, y_j) = \{l_x \leq x_j \leq u_x\} \cap \{l_y \leq y_j \leq u_y\} \quad (18)
\]

where \(l_x\) and \(l_y\) are the lower bounds of the \(x\) and \(y\) coordinates, respectively, of the \(j\)-th forbidden area, and \(u_x\) and \(u_y\) are the upper bounds of the \(x\) and \(y\) coordinates, respectively, of the \(j\)-th forbidden area.

FIGURE 4. UAV maneuverability parameters: (a) turning angle, and (b) flying slope.

3) TURNING ANGLE CONSTRAINT
The turning angle is defined as the horizontal angle between the previous and current directions (as seen in Figure 4). A practical path should be adequately smooth for the UAV to maneuver through easily. Therefore, the turning angle of the UAV is required to be less than the maximum tolerant turning angle. This constraint can be formulated with (19):

\[
TAC = 0, \quad TAC = \sum_{i=2}^{N_w-1} TAC_i,
\]

where \(TAC_i = \begin{cases} Q, & \text{if } \theta_i > \theta_{\text{max}} \\ 0, & \text{otherwise} \end{cases} \quad (19)
\]

where \(\theta_i\) is the turning angle at the \(i\)-th waypoint \((x_i, y_i, z_i)\), and \(\theta_{\text{max}}\) is the maximum tolerable turning angle. In [16], Zheng at al. suggested the formulation of \(\theta_i\) is (20), as shown at the bottom of this page, where \(\|x\|_2\) is the norm of vector \(x\).

4) FLYING SLOPE CONSTRAINT
Analogous to the turning angle in the horizontal direction, we introduce flying slope to indicate UAV maneuverability
in the vertical direction, i.e., gliding and climbing angle. The flying slope is defined as the slope between the horizontal direction of the current waypoint to the next one (as shown in Figure 4). The flying slope must be within the scope of the maximum gliding and climbing angles. The flying slope constraint (FSC) can be formulated with (21):

\[
FSC = 0, \quad FSC = \sum_{i=2}^{N_w} FSC_i
\]

where \( FSC_i = \begin{cases} 
Q, & \text{if } r_i \notin [\tan(\alpha_{\text{max}}), \tan(\beta_{\text{max}})] \\
0, & \text{otherwise}
\end{cases}
\] (21)

where \( \alpha_{\text{max}} \) and \( \beta_{\text{max}} \) are the maximum tolerable gliding and climbing angles, respectively, and \( r_i \) is the flying slope at the \( i \)th waypoint \((x_i, y_i, z_i)\). Zheng et al. [16] suggested a formulation of it as seen in (22):

\[
r_i = \frac{z_i - z_{i-1}}{\| (x_i - x_{i-1}, y_i - y_{i-1}) \|_2}
\] (22)

5) MULTIPLE UAV COLLISION AVOIDANCE CONSTRAINT

Our focus is on trajectory planning for multiple UAVs. When multiple UAVs are used for a complex surveillance mission, the paths should be carefully designed for the drones in order to avoid collisions among them, which can be vital for task implementation. For two separate trajectories, UAVs should maintain a minimum safe distance between them to avoid collisions. This constraint can be described as follows:

\[
CAC = 0, \quad CAC = \sum_{i=1}^{N_p} \sum_{j=1}^{N_q} CAC_i
\]

where \( CAC_i = \begin{cases} 
Q, & \text{if } d_{ij}^{\text{min}} < d_{\text{min}} \\
0, & \text{otherwise}
\end{cases}
\]

\[
d_{ij}^{\text{min}} = \sqrt{(x_j^m - x_i^m)^2 + (y_j^m - y_i^m)^2 + (z_j^m - z_i^m)^2}
\] (23)

where \( d_{\text{min}} \) is the minimum safe distance to avoid collisions, \( d_{ij}^{\text{min}} \) is the cartesian distance between the \( i \)th waypoint of the \( u \)-th UAV trajectory and the \( j \)th waypoint of the \( p \)-th UAV trajectory.

IV. PROPOSED MCHP-RA SCHEME SURVEILLANCE AREA PRIORITY UPDATING MECHANISM BASED ON EVENT DETECTION

In this section, we propose a surveillance area priority updating mechanism based on the detection of an event. When an MDr detects the existence of IDrs in a certain area (i.e., an event is detected in the area), on intuition, it will be more attentive to that area during the next flight, or it shares the information with other MDrs. Additionally, an MDr should also pay more attention to the areas where SAI values are rapidly changing compared to their historical average SAI values. Moreover, it is necessary to increase the SAI values for those areas that have not been surveilled for more than a certain number of flights so that MDrs can cover them during the next flight. To increase surveillance efficiency, we reduce the SAI values for those areas that were previously surveilled to avoid repeated surveillance of the same areas. Based on the above requirements, we define four cases for updating SAI values.

- When IDrs are detected in a certain cell, surveil its neighboring cells to prevent IDrs from intruding into those areas. Therefore, increase the SAI values of that cell as well as its neighboring cells.
- If the SAI value of one cell changes rapidly compared to its previous average historical SAI values, then the SAI value of that cell is adjusted.
- When a cell has not been surveilled for more than a specific flight times, we should increase its SAI value.
- If a cell has been surveilled, we should reduce its SAI value.
H. Teng et al.: 3D Optimal Surveillance Trajectory Planning for Multiple UAVs by Using PSO

FIGURE 6. PSO trajectory optimization performance in terms of (a) energy consumption, (b) flight risk, and (c) surveillance area importance (SAI).

Based on the above descriptions, we formulate those cases as follows.

For the first case, when $|SAI_i(t) - SAI_i(t-1)| > th_{event}$, then an event has happened in those cells that have been supervised from the $i^{th}$ waypoint, and the SAI values of those cells can be updated by using (24):

$$v_{cell\ x\ (t)} = \max[v_{max}, \gamma_1 \times v_{cell\ x\ (t-1)}], \ \gamma_1 > 1 \ (24)$$

where $SAI_i(t)$ is the SAI value of the $i^{th}$ waypoint during the $t^{th}$ flight time, $v_{cell\ x\ (t)}$ represents the SAI value of cell $x$ during the $t^{th}$ flight time, and $th_{event}$ and $v_{max}$ are the event detection threshold and the maximum SAI value, respectively.

For the second case, when the absolute value between the current SAI value of cell $x$ and its previous historical average SAI value is more than the predetermined updating threshold, $th_{update}$, then its SAI value is updated by the value returned by $\max[v_{max}, f_{cell\ x\ (t)}]$, so we formulate the second case with (25) and (26):

$$v_{cell\ x\ (t)} = \begin{cases} 
\gamma_2 v_{ini\ cell\ x}, & \text{if } |V_{cell\ x\ (t-2)} - v_{cell\ x\ (t-1)}| < th_{update} \\
\max[v_{max}, f_{cell\ x\ (t)}], & \text{otherwise}
\end{cases} \ (25)$$

$$f_{cell\ x\ (t)} = \log(\lambda \times |V_{cell\ x\ (t-2)} - v_{cell\ x\ (t-1)}| + 1) \times v_{cell\ x\ (t-1)} \ (26)$$

where $V_{cell\ x\ (t-2)}$ represents the average SAI value from the first flight time to $(t-2)$ th flight time, $v_{ini\ cell\ x}$ is the initial SAI value of cell $x$, and $\lambda$ is the constant control parameter.

For the third case, when a cell has not been surveilled for more than a certain flight times threshold $th_{flight}$, then we increase its SAI value using (27):

$$v_{cell\ x\ (t)} = \max[v_{max}, \gamma_2 \times v_{cell\ x\ (t-1)}], \ \gamma_2 > 1 \ (27)$$

For the fourth case, when a cell has been surveilled, its SAI value is reduced by calculating (28):

$$v_{cell\ x\ (t)} = \min[v_{min}, \gamma_3 \times v_{cell\ x\ (t-1)}], \ \gamma_3 < 1 \ (28)$$

V. PROPOSED PSO-BASED TRAJECTORY PLANNER

In this section, we propose a trajectory planner for multiple UAVs based on standard PSO and the surveillance area priority updating mechanism explained in Section IV. The proposed planner first utilizes PSO to derive the optimal trajectories for each MDr, in which the proposed multi-objective fitness function is used to acquire the best flying waypoint sequence from all possible trajectories. Then CAC is exploited to detect the existence of collisions. If CAC is satisfied, the planner will generate the optimal trajectories for one flight time. Finally, the SAI values will be updated before the next flight. Details are explained in following subsections.

A. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization is a widely used evolutionary heuristic search algorithm for solving optimization problems, and was initially proposed by Kennedy and Eberhart in 1995 [48]. In PSO, each particle corresponds to a candidate solution that is randomly initialized. Then, in each iteration, the velocity and position of each particle are renewed based on information about the previous velocity, the best position ever occupied by the particle (personality influence), and the best position ever occupied by any particle in the...
swarm (social swarm). The mathematical formulations are as follows.

Assume the number of particles is $P$, the dimensionality of particles is $D$, and the iteration number is $N$. For the $i$-th particle, $x_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$ and $v_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$ represent the velocity and position vectors, respectively. For standard PSO, there are two kinds of cost value, i.e., individual best value, $P_{i\text{, best}}$, of one particle, and swarm best value, $S_{\text{best}}$, of all particles, which are depicted in (29):

$$P_{i\text{, best}} = (p_{i1, \text{best}}, p_{i2, \text{best}}, \ldots, p_{iD, \text{best}})$$

$$S_{\text{best}} = (s_{1, \text{best}}, s_{2, \text{best}}, \ldots, s_{D, \text{best}})$$ (29)

Once the two cost values are determined, the velocity and position of each particle in each dimension are renovated by using (28).

$$v_{ij}^{k+1} = \omega v_{ij}^k + c_1 r_1 (p_{ij, \text{best}} - x_{ij}^k) + c_2 r_2 (s_{j, \text{best}} - x_{ij}^k)$$

$$x_{ij}^{k+1} = x_{ij}^k + v_{ij}^{k+1}$$

where $i = 1, 2, \ldots, P$ $j = 1, 2, \ldots, D$

$k = 1, 2, \ldots, N$ (30)

In (30), $r_1$ and $r_2$ are random values between 0 and 1; $\omega$ is the inertia parameter, which reflects the influence of the velocity of the previous iteration on the current iteration; and $c_1$ and $c_2$ represent self-cognition and social knowledge, which indicate the inheriting abilities from the particle itself and from the whole swarm.

B. PROPOSED TRAJECTORY PLANNER

In our proposed planner, a feasible flight route consists of a sequence of waypoints and line segments. During our implementation, an eight-waypoint trajectory is adopted. We divide the entire operational area into unit cell areas.

The process of the proposed planner is shown in the algorithm pseudocode. At the beginning, we set estimated surveillance flight times to cover the whole operational area, and we initialize the SAI values for all cells. Next, we utilize PSO to derive the optimal trajectories for multiple MDrs, which corresponds to steps 5 to 33. During the optimization process, we first randomly generate the position and velocity vectors for $N_{\text{par}}$ particles, and initialize $P_{i\text{, best}}$ and $S_{\text{best}}$ as $x_t$ and $x_{N_{\text{par}}}$, respectively. Next, the position and velocity vectors of each particle are renovated by using Formula (27). Then, the proposed multi-objective fitness functions are used to evaluate those newly updated particles, which consist of several objective and constraint functions explained in Section IV.

After that, we renew $P_{i\text{, best}}$ and $S_{\text{best}}$ based on the fitness values of all the particles. Then, we store the optimal trajectory for the first MDr while the iteration number is set equal to $N_{\text{iter}}$. Finally, to avoid waypoint overlapping among multiple MDrs, i.e., repeated surveillance of the same area, we reduce the SAI values of those cells that have been surveilled before starting the next trajectory planning. Thus, the surveillance efficiency is improved. Since our research mainly focuses on collision-free path planning for multiple UAVs, the collision avoidance constraint is applied to determine if collisions could occur between MDr trajectories.
Algorithm 1 Pseudocode of the Proposed Multi-UAV Trajectory Planner

1: Set flight time = $N_{flight}$;
2: Initialize the SAI value of each cell;
3: for $i = 1: N_{flight}$
4: {  
5: while (CAC is not satisfied)
6: {  
7: Set monitoring UAV number = $N_{MDr}$;
8: for $j = 1: N_{MDr}$
9: {  
10: Set iteration number = $N_{iter}$;
11: Set particle number = $N_{par}$;
12: for $k = 1: N_{iter}$
13: {  
14: for $t = 1: N_{par}$
15: {  
16: Randomly initialize $x_t$ and $v_t$;
17: Initialize $P_{t,best} = x_t$, $S_{best} = x_{N_{par}}$;
18: Update $x_t$ and $v_t$ using (30);
19: Compute the fitness value of $x_t$ using (3) to (22);
20: if fitness($x_t$) > fitness($P_{t,best}$)  
21: {$P_{t,best} = x_t$;  
22: if (fitness($P_{t,best}$) > fitness($S_{best}$)  
23: {$  
24: S_{best} = P_{t,best}$;  
25: Opt.fitness = fitness($S_{best}$);  
26: }  
27: }  
28: }  
29: Update the SAI values using (28);
30: }  
31: Evaluate collisions among multiple UAVs using (23);
32: }  
33: Generate the output of collision-free trajectories for multiple MDRs;
34: Update the SAI values using equations (24) to (27);
35: }  
36: Generate the output of the $N_{flight}$ flight times path planning results;

If CAC is not satisfied, we go back to Step 5. The optimal trajectories for multiple MDRs can be obtained only if CAC is satisfied. After that, SAI values should be renewed before executing the next flights by using formulas (22) to (25). Finally, when the flight time is equal to $N_{flight}$, it will generate all of the optimal planning trajectories for multiple MDRs to cover the whole operational area except for the restricted areas.

VI. SIMULATION RESULTS
In this section, we conducted a Matlab simulation for two MDRs over several flights times to evaluate the performance of the proposed multiple-UAV trajectory planner. First, we evaluated the optimal trajectory solution generated by the proposed planner, and then, we verify the rationality of the proposed SAI updating mechanism based on the generated trajectories. For PSO parameter settings, Roberge et al. [19] suggested $c_1 = c_2 = 1.496$ and $\omega = 0.7298$. The main parameters used for the simulation are shown in Table 2.
In Figure 5, we show how the number of particles affects the optimal fitness value of the proposed fitness function. As expected, the fitness value converges to a stable value faster as the numbers of iterations and particles increase. Figure 6 shows the trajectory optimization performance of the first flight time in terms of energy consumption, flight risk, and surveillance area importance, in which the particle number is 256. As the number of iterations increases, the energy consumption and flight risk for the two MDRs minimize and maintain a stable value while their surveillance area importance values are maximized. Moreover, the SAI values of the optimal trajectories for the two MDRs are 191 and 187, while their energy consumption difference is less than five, which means the proposed trajectory planner can ensure fairness between generated trajectories. In our paper, we generate all the trajectories in a 3D environment as illustrated in Figure 7, which represents the optimal trajectory of the first flight.

In Figure 8, we show the surveillance trajectories of the two MDRs in accordance with event detection for the first three flight times. The forbidden areas and the event detection areas are marked by blue and red rectangles, respectively. Figure 8 (a) and (b) show the optimal trajectories for the two MDRs during the first and second flight time, respectively. We can see that the waypoints from the two flights do not overlap, which means that our proposed trajectory planner can surveil the operational area with high efficiency. We triggered two events at point (9,15) and (9,13) (i.e., the event-detection area) after the second flight. In Figure 8 (c), the MDRs visit those two points during the third flight time, which indicates that our proposed SAI updating mechanism can cover the operational area where the events happened.

For each flight time, we sum the optimal fitness values of the two MDRs. In Figure 9, we compare the cumulative fitness value of the fixed SAI and the dynamic SAI.

![Figure 9. Cumulative fitness value comparison between the fixed SAI and the dynamic SAI.](image-url)
optimal fitness values between the fixed SAI and the dynamic SAI to validate the effectiveness of the proposed SAI updating method. As the flight time increases, the cumulative fitness value for dynamic SAI increases faster, indicating that our proposed updating SAI method can help MDrs visit the more important areas in a changing environment.

VII. CONCLUSION

In this paper, we propose a trajectory planner for multiple UAVs and apply it to MDrs to surveil a certain operational area. To evaluate the trajectories generated by the proposed trajectory planner, we then introduce a multi-objective fitness function that has eight optimization indexes in terms of UAV maneuverability, energy consumption, flying risk, and surveillance area priority. The optimal trajectories are obtained by maximizing the fitness function values. Moreover, we also propose a surveillance area importance updating mechanism to effectively consider new events that happen in the operational area. The simulation results prove that our proposals can obtain collision-free trajectories for multiple UAVs with high fitness values, and they show highly dynamic environmental adaptability. Currently, we considered the two MDrs over several flights times to evaluate the performance of the proposed multiple-UAV trajectory planner. We meant to figure out the feasibility of the three dimension optimal surveillance trajectory planning for multiple UAVs by using PSO with surveillance area priority. We will consider more than two MDrs in our future work because our proposal can effectively perform to achieve the collision-free trajectories for multiple UAVs with high fitness values and adapting the highly dynamic environment.

REFERENCES

[1] H. Xiang and L. Tian, “Development of a low-cost agricultural remote sensing system based on an autonomous unmanned aerial vehicle (UAV),” Biosyst. Eng., vol. 108, no. 2, pp. 174–190, Feb. 2011.

[2] Q. Yang and S.-J. Yoo, “Optimal UAV path planning: Sensing data acquisition over IoT sensor networks using multi-objective bio-inspired algorithms,” IEEE Access, vol. 6, pp. 13671–13684, 2018.

[3] C. Zhan, Y. Zeng, and R. Zhang, “Energy-efficient data collection in UAV enabled wireless sensor network,” IEEE Wireless Commun. Lett., vol. 7, no. 3, pp. 328–331, Jun. 2018.

[4] H. He, S. Zhang, Y. Zeng, and R. Zhang, “Joint altitude and beamwidth optimization for UAV-enabled multiuser communications,” IEEE Commun. Lett., vol. 22, no. 2, pp. 344–347, Feb. 2018.

[5] J. Lu, Y. Zeng, R. Zhang, and T. J. Lim, “Placement optimization of UAV-mounted mobile base stations,” IEEE Commun. Lett., vol. 21, no. 3, pp. 604–607, Mar. 2017.

[6] E. P. de Freitas, T. Heimfarth, I. F. Netto, C. E. Lino, C. E. Pereira, A. M. Ferreira, F. R. Wagner, and T. Larsson, “UAV relay network to support WSN connectivity,” in Proc. Int. Congr. Ultra Modern Telecommun. Control Syst., Moscow, Russia, Oct. 2010, pp. 309–314.

[7] I. Maza, F. Caballero, and J. Capitan, “Experimental results in multi-UAV coordination for disaster management and civil security applications,” J. Intell. Robot. Syst., vol. 61, nos. 1–4, pp. 563–585, Jan. 2011.

[8] D. Popescu, L. Ichim, and T. Caramfilache, “Flood areas detection based on UAV surveillance system,” in Proc. 19th Int. Conf. Syst. Theory, Control Comput. (ICSTCC), Cheile Gradistei, Oct. 2015, pp. 753–758.

[9] H. X. Pham, H. M. La, D. Feil-Seifer, and M. Deans, “A distributed control framework for a team of unmanned aerial vehicles for dynamic wildfire tracking,” in Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS), Vancouver, BC, Canada, Sep. 2017, pp. 6648–6653.

[10] T. Turker, O. K. Sahingoz, and G. Yilmaz, “2D path planning for UAVs in radar threatening environment using simulated annealing algorithm,” in Proc. Int. Conf. Unmanned Aircr. Syst. (ICUAS), Denver, CO, USA, Jun. 2015, pp. 56–61.

[11] S.-J. Yoo, J.-H. Park, S.-H. Kim, and A. Shrestha, “Flying path optimization in UAV-assisted IoT sensor networks,” IET Exp., vol. 2, no. 3, pp. 140–144, Sep. 2016.

[12] J. Carsten, D. Ferguson, and A. Sintez, “3D field D: Improved path planning and replanning in three dimensions,” in Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst., Beijing, China, Oct. 2006, pp. 3381–3386.

[13] K. Yang and S. Sukkarieh, “Real-time continuous curvature path planning of UAVs in cluttered environments,” in Proc. 5th Int. Symp. Mechatronics Appl., May 2008, pp. 1–6.

[14] Q. Wang, A. Zhang, and L. Qi, “Three-dimensional path planning for UAV based on improved PSO algorithm,” in Proc. 26th Chin. Control Decis. Conf. (CCDC), Changsha, China, May 2014, pp. 3981–3985.

[15] X. Chen, R. Xu, and J. Zhao, “Multi-objective route planning for UAV,” in Proc. 4th Int. Conf. Inf. Sci. Control Eng. (ICISCE), Changsha, China, Jul. 2013, pp. 1023–1027.

[16] C. Zheng, L. Li, F. Xu, F. Sun, and M. Ding, “Evolutionary route planner for unmanned air vehicles,” IEEE Trans. Robot., vol. 21, no. 4, pp. 609–620, Aug. 2005.

[17] E. Besada-Portas, L. de la Torre, J. M. de la Cruz, and B. de Andrés-Toro, “A new evolutionary trajectory replanner for multiple UAVs in realistic scenarios,” IEEE Trans. Robot., vol. 26, no. 4, pp. 619–634, Aug. 2010.

[18] P. Yang, K. Tang, J. A. Lozano, and X. Cao, “Path planning for single unmanned aerial vehicle by separately evolving waypoints,” IEEE Trans. Robot., vol. 31, no. 5, pp. 1130–1146, Oct. 2015.

[19] V. Roberge, M. Tarbouchi, and G. Labonte, “Comparison of parallel genetic algorithm and particle swarm optimization for real-time UAV path planning,” IEEE Trans. Ind. Informat., vol. 9, no. 1, pp. 132–141, Feb. 2013.

[20] R. J. Szczesniak, “Threat netting for real-time, intelligent route planners,” in Proc. Inf. Decis. Control. Data Inf. Fusion Symp., Signal Process. Commun. Decis. Control Symp., Adelaide, SA, Australia, 1999, pp. 377–382.

[21] X. Li, Y. Zhao, J. Zhang, and Y. Dong, “A hybrid PSO algorithm based flight path optimization for multiple agricultural UAVs,” in Proc. IEEE 28th Int. Conf. Tools with Artif. Intell. (ICTAI), San Jose, CA, USA, Nov. 2016, pp. 691–697.

[22] S. Rohde, “Signal monitoring of radio controlled civilian unmanned aerial vehicles and possible countermeasures,” in Proc. Protecting Sky Whitepaper, vol. 2, 2015, pp. 1–14.

[23] E. William and M. Hoffman, “Classification of military ground vehicles using time domain harmonics’ amplitudes,” IEEE Trans. Instrum. Meas., vol. 60, no. 11, pp. 3720–3731, May 2011.

[24] A. Averbuch and A. Zheludev, “Wavelet-based acoustic detection of moving vehicles,” J. Multidimensional Syst. Signal Process., vol. 20, no. 1, pp. 55–80, 2009.

[25] E. Chaves, M. Travieso, and A. Camacho, “Katydid acoustic classification on verification approach based on MFCC and HMM,” in Proc. IEEE Conf. Intell. Eng. Syst., Lisbon, Portugal, 2012, pp. 561–566.

[26] C. Lin and H. Chen, “Audio classification and categorization based on wavelets and support vector machine,” IEEE Trans. Speech Audio Process., vol. 13, no. 5, pp. 644–651, Aug. 2005.

[27] I. Sen, M. Saracilar, and P. Kalyva, “A comparison of SVM and GMMS-based classifier configurations for diagnostic classification of pulmonary sounds,” IEEE Trans. Biomed. Eng., vol. 62, no. 7, pp. 1768–1776, Feb. 2015.

[28] A. Aljaafreh and L. Dong, “Ground vehicle classification based on Hierarchical Hidden Markov Model and Gaussian Mixture Model using wireless sensor networks,” in Proc. IEEE Int. Conf. Electro/Inf. Technol. (ICEIT), IL, USA, May 2010, pp. 1–4.

[29] Z. Kaleem and M. H. Rehmani, “Amateur drone monitoring: State-of-the-art architectures, key enabling technologies, and future research directions,” IEEE Wireless Commun., vol. 25, no. 2, pp. 150–159, Apr. 2018, doi: 10.1109/MWC.2018.1700152.

[30] I. Ahmad, W. Chen, and K. H. Chang, “Co-channel interference analysis using cooperative communication schemes for the coexistence of PS-LTE and LTE-R networks,” in Proc. IEEE Commun. Electron. Special Session LTE Technol. Services, Jul. 2016, pp. 181–182.

[31] I. Ahmad, W. Chen, and K. Chang, “LTE-railway user priority-based cooperative resource allocation schemes for coexisting public safety and railway networks,” IEEE Access, vol. 5, pp. 7985–8000, 2017, doi: 10.1109/ACCESS.2017.2698989.
[32] Z. Kaleem, M. Khalig, A. Khan, I. Ahmad, and T. Duong, “PS-CARA: Context-aware resource allocation scheme for mobile public safety networks,” Sensors, vol. 18, no. 5, p. 1473, May 2018, doi: 10.3390/s18051473.

[33] I. Ahmad, Z. Kaleem, and K. Chang, “Unlink power control for interference mitigation based on users priority in two-tier femtocell network,” in Proc. Int. Conf. Ict Converg. (ICICT), Oct. 2013, pp. 474–475.

[34] I. Ahmad and K. Chang, “Analysis on MIMO transmit diversity and multiplexing techniques for ship ad-hoc networks under a maritime channel model in coastline areas,” in Proc. Int. Conf. Inf. Commun. Technol. Converg. (ICTC), Oct. 2017, pp. 18–20.

[35] I. Ahmad and K. H. Chang, “Analysis on MIMO transmit diversity techniques for ship ad-hoc network under a maritime channel model in coastline areas,” J. Korean Inst. Commun. Inf. Sci., vol. 42, no. 2, pp. 383–385, Feb. 2017, doi: 10.1109/JICT.2017.8190820.

[36] I. Ahmad, Z. Kaleem, and K. Chang, “QoS priority based femtocell user power control for interference mitigation in 3GPP LTE—A HetNet,” J. Korean Inst. Commun. Inf. Sci., vol. 39B, no. 2, pp. 61–74, Feb. 2014, doi: 10.7840/jkics.2014.39B.2.61.

[37] W. Chen, I. Ahmad, and K. Chang, “Co-channel interference management using eICIC/FelCIC with coordinated scheduling for the coexistence of PS-LTE and LTE-R networks,” EURASIP J. Wireless Commun. Netw., vol. 2017, no. 1, pp. 1–14, Dec. 2017. 10.1186/s13638-017-0822-6.

[38] I. Ahmad, Z. Kaleem, R. Narmeen, L. D. Nguyen, and D.-B. Ha, “Quality-of-service aware game theory-based uplink power control for 5G heterogeneous networks,” Mobile Netw. Appl., vol. 24, no. 2, pp. 556–563, Apr. 2019, doi: 10.1007/s11036-018-1156-2.

[39] I. Ahmad and K. Chang, “Effective SNR mapping and link adaptation strategy for next-generation underwater acoustic communications networks: A cross-layer approach,” IEEE Access, vol. 7, pp. 44150–44164, 2019, doi: 10.1109/ACCESS.2019.2908018.

[40] I. Ahmad and K. Chang, “Design of system-level simulator architecture for underwater acoustic communications and networking,” in Proc. Int. Conf. Inf. Commun. Technol. Converg. (ICTC), Oct. 2016, pp. 384–386.

[41] U. A. Mughal, I. Ahmad, and K. H. Chang, “Virtual cells operation for 5G V2X communications,” in Proc. Conf. Korean Inst. Commun. Inf. Sci. (KICS), Pyongyang, Jan. 2019, pp. 1–2.

[42] U. A. Mughal, I. Ahmad, and K. H. Chang, “Cellular V2X communications in unlicensed spectrum: Compatible coexistence with VNET in 5G systems,” in Proc. ICCI, Seoul, Korea, May 2019, pp. 1–2.

[43] I. Ahmad and K. Chang, “Mission critical user priority-based random access scheme for collision resolution in coexisting PS-LTE and LTE-M networks,” IEEE Access, vol. 7, pp. 115505–115517, 2019.

[44] I. Ahmad and K. H. Chang, “Downlink power allocation strategy for next-generation underwater acoustic communications networks,” Electronics, vol. 8, pp. 1–14, Nov. 2019.

[45] I. Ahmad and K. Chang, “Mission-critical user priority-based cooperative resource allocation schemes for multi-layer next-generation public safety networks,” Phys. Commun., vol. 38, Feb. 2020, Art. no. 100926.

[46] Y. He, I. Ahmad, L. Shi, and K. H. Chang, “SVM-based drone sound recognition using the combination of HLA and WPT techniques in practical noisy environment,” KSII Trans. Internet Inf. Syst., vol. 13, no. 10, pp. 5078–5094, May 2019.

[47] S. Golzari, M. N. Zardehsavar, A. Mousavi, M. R. Saybani, A. Khalili, and S. Shamshirband, “KGSAs: A gravitational search algorithm for multimodal optimization based on K-Means Nicheing technique and a novel elitism strategy,” Open Math., vol. 16, no. 1, pp. 1582–1606, Dec. 2018.

[48] J. Kennedy and R. Eberhart, “Particle swarm optimization,” in Proc. Neural Netw., 1995, pp. 1942–1948.

HU TENG received the B.S. degree in communication engineering from the Chongqing University of Posts and Telecommunications, China, in 2016, where he is currently pursuing the M.S. degree in mobile communication technology.

From 2017 to 2018, he was an Exchange Student with Electronic Engineering Department, Inha University, South Korea. His research interests include mobile ad-hoc networks for UAV and anti-drone technology using AI.

ISHTIAQ AHMAD received the B.S. degree in electrical engineering from the University of Engineering and Technology (UET), Peshawar, Pakistan, in 2007, and the M.S. and Ph.D. degrees in electronic engineering from Inha University, South Korea, in 2014 and 2019, respectively.

From 2007 to 2008, he was a BSS Engineer with the O&M Department, Zong Pakistan. Since 2009, he has been a Lecturer with the Faculty of Engineering and Technology (FET), Gomal University, Pakistan. He is currently working as the Chairman of Electrical Engineering Department and the Dean of the Faculty of Engineering and Technology, Gomal University, Pakistan. He has authored several international journals and IEEE conference papers and also holds U.S. and Korean patents. His research interests include interference management in 3GPP LTE-A and 5G systems, public safety and mobile ad-hoc networks (especially for UAV), cellular-V2X technology, and maritime and underwater communications.

Dr. Ahmad was a recipient of the Jungseok International Scholarship to pursue his M.S. and Ph.D. degrees at Inha University, due to his excellent academic career. He received the Outstanding Research Award and the Excellent Student Award from Inha University, in 2019, for his excellence of journal publication and outstanding research achievements.

ALAMGIR MSM received the B.S. degree in electronics engineering from Kongju National University, South Korea, in 2016, and the M.S. degree from the Mobile Telecommunication Research Laboratory (MTRL), Department of Electronics Engineering, Inha University, South Korea.

He is currently a Chief Research Engineer with Entec Electric and Electronic Company Ltd. His research interests include mobile ad-hoc networks for UAV and anti-drone technology using AI, and link adaptation on underwater communication using machine learning. He was a recipient of the Korean Government Scholarship Program (KGSP) and the Jungseok International Scholarship to pursue his B.S. and M.S. degrees, due to his excellent academic career.

KYUNGHI CHANG (Senior Member, IEEE) received the B.S. and M.S. degrees in electronics engineering from Yonsei University, Seoul, South Korea, in 1985 and 1987, respectively, and the Ph.D. degree in electrical engineering from Texas A&M University, College Station, TX, USA, in 1992.

From 1989 to 1990, he was with the Samsung Advanced Institute of Technology (SAIT) as a member of the research staff and was involved in digital signal processing system design. From 1992 to 2003, he was with the Electronics and Telecommunications Research Institute (ETRI) as a Principal Member of the technical staff, where he led the design teams involved in the WCDMA UE modem and 4G radio transmission technology (RTT). He is currently with Electronic Engineering Department, Inha University. His research interests include radio transmission technology in 3GPP LTE-A and 5G systems, public safety and mobile ad-hoc networks (especially for UAV), cellular-V2X technology, maritime and underwater communications, and applications of AI technologies.

Dr. Chang was a recipient of the LG Academic Awards, in 2006, the Hae-dong Best Paper Awards, in 2007, the IEEE ComSoc Best Paper Awards, in 2008, the Hae-dong Academic Awards, in 2010, and the SKT SafeNet Best Idea Awards, in 2015. He is currently the Chairman of the Expert Committee in SafeNet Forum and the Mobile and Automotive Convergence Committee in 5G Forum. He has served as the Editor-in-Chief and an Executive Director for the Journal of Korean Institute of Communications and Information Sciences (KICS), from 2010 to 2012 and in 2013, respectively, and the Vice President at the KICS, from 2017 to 2018. He has also served as an Editor of ITU-R T.101 IMT.MOD.