Multiple UAVs Tracking for Moving Ground Target

Dongqiao Bai, Jikun Tian, Ding Li, and Shouzhi Li

Abstract— **To track the ground objects through a single aerial vehicle doesn't give better results especially when the speed of the object is very fast. To solve this issue, this research article presents Improved Grey Golf Optimizer (IGWO) approach to track the ground moving objects through multiple Unmanned Aerial Vehicles (UAVs). In this manuscript, target tracking is modeled by expressing the target model, sensor coverage region, restricted region, and space constraints. In IGWO algorithm, only the globally best position is considered for the tracking which provides better results as well as faster response. The algorithm also reproduces the wolf pack's destructive strategy and social hierarchy to find the optimal solution for the system. To validate the effectiveness of the proposed system various scenarios with different ground vehicle motion has been tested. Three UAVs simultaneously track the ground object, its direction, and motion along the followed path. In future work, the adaptive approach can be used to identify obstacle detection for UAVs and ground objects.**

Index Terms—**Unmanned aerial vehicle (UAV), Multi-UAVs, Improved grey wolf optimizer (IGWO), tracking**

I. INTRODUCTION

UNMANNED Aerial Vehicles (UAVs) progressively demands and utilized in military and civilian fields [1] in previous decades for example in rescue and search assignment [2], surveillance [3], inspection, and exploration [4]. Unmanned vehicles attain high flexibility and safety with low cost as compared to manned vehicles. Many studies focus on improving levels of unmanned vehicles in terms of autonomy and aptitude. Recently, multi-UAVs target tracking becomes a hot research topic [5] including the technology of target tracking by multi-sensor fusion [6], path planning, and image processing [7]. The study focuses on problematic trajectory optimization to preserve the moving target being sensed by UAV.

The performance of multiple UAV tracking improves expressively as compared to the case in which a single UAV performs the task. During the flight mission, vehicles share information thus the sensor coverage also increases [8]. The two modes of target tracking are the centralized approach and the decentralized approach. In the centralized approach [9], the center node assigns the missions to proxies in the team as in this manuscript. Similarly in the decentralized approach [10], every proxy plans its path based on the information from other vehicles.

Various studies propose path planning algorithms for the target tracking of UAVs. In reference [11], the paper presents non-linear disturbance, observer-based standoff tracking, and guidance for multi-fixed-wing UAVs. Moreover, the disturbance observer approximates the wind disturbance. Similarly, the Lyapunov guidance vector recompense effect of wind and monitors the target. The simulation results show the flight experiments to explain the performance of the proposed scheme. About [12], this study proposes a swarm intelligence-based optimization algorithm to improve the tracking trajectory of UAVs. It helps in maintaining the distance between the UAVs and also improves the tracking process. Another improved bat algorithm is proposed in this manuscript to overcome the drawbacks like poor stability. The experiments are conducted with the preferred distance between the UAV and target. The experimental results show effective results in tracking. Similarly in [13], target searching and path planning is the main issue to be focused on. This manuscript proposes an online distributed algorithm for searching and tracking. This study also proposed a quantum probability model to define the target position. Furthermore, it derived the tree algorithm to solve the optimal route. Experiments and different analyses elaborate on the accuracy and effectiveness of the proposed scheme. Finally, in reference [14-15], the study focuses on the tracking problem of multi-UAVs based on formation control. It also defines the methodology of formation control to show the effective tracking results of the target. It also adopts the formation control method based on the leader-follower system. The MATLAB simulation proves the formation control and tracking strategy of the proposed scheme.

The main contribution of this manuscript is that it designs a novel algorithm that solves the challenging problem of tracking. Firstly, this manuscript models the problem by considering the target model, sensor coverage region, restricted region, and space constraints. Secondly, this manuscript utilizes an improved grey wolf optimizer (IGWO) as the tracking problems solver. Finally, the simulation results show the fitness of the proposed algorithm which describes its betterment and reliability.

The manuscript is planned as follows. The introduction is presented in section 1. The problem definition and its proposed solution are defined in section 2. Section 3 defines state of the art. Section 4 defines the mathematical formulation. Section 5 defines the proposed scheme i.e. IGWO. The simulations are done in section 6. Section 7 presents the conclusion of this manuscript.

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II. PROBLEM DEFINITION AND PROPOSED SOLUTION

This section of the manuscript defines the problem definition and proposed solution used in this research article. During the tracking mission of multi-UAVs, the trajectory optimization problem [16] is considered. Thus the main focus is to solve these problems and maintain the target being spotted as much as possible. To solve all these problems, the study designs and adopts the IGWO method. Similarly, it also models the target tracking problem by considering the target model, sensor coverage region, and space constraints. The designed algorithm attains better performance and efficiency by introducing some enhancement approaches.

III. STATE OF THE ART

This section defines the recent trends in this field. In reference [17], the study proposes a path planning method for tracking moving targets. The movement of the target, turning rate, and speed are considered as inputs. The environment attains the obstacles which becomes the line of sight (LOS) of the sensor. It also focuses on the energy saving of the system with the help of sensors and control inputs. Furthermore, the study proposes the model; Distributed Model Predictive Control (DMPC) to attain the best path for individual UAVs. In [18-19], the study explains the UAV searching for a moving target with known speed and heading towards its path. The roads are detached with ground sensors to detect the motion of the target. It presents the Recursive Forward Search (RFS) method. The method scales ailing in problem constraints that are the number of nodes and evader path. The results show the applicability of the proposed scheme. About [20], the study solves the target tracking problem of a ground target. The study proposes an ant colony optimization (ACO) algorithm to plan an effective track for the target. It also defined the predicted meeting point to solve moving target problems. Finally, simulations results show a comparison of the designed scheme with other schemes. The proposed method plans an effective and optimal path and solves the improbability problems. It also improves the multi-UAV path planning. Finally, in [21-22], the study proposes a path planning method with a team of UAVs. The proposed scheme offers to plan trajectories and provides coordination between vehicles. The novel method namely non-linear formulation is proposed to overcome all the changes. This method is integrated with hardware and software. The study also provides computational results in field and simulation experiments. Results show that the proposed method attains the capability to make optimal trajectories.

IV. MATHEMATICAL FORMULATION

This section of the manuscript explains the multi-UAV's tracking target in the formulated form. This section comprises UAV kinematics and dynamics [23], target model, sensor coverage & restricted region, and space limitations among UAVs.

A. UAV Kinematics and Dynamics

Considering the kinematics of UAVs in two-dimensional space. The UAV's kinematics geometry is demonstrated as the dynamical system in discrete-time and can be attained by the following equation.

$$\bar{x}_i(t+1) = f(\bar{x}_i(t), u_i(t) \quad \therefore i = \{1, \ldots., n_{UAV}\} \tag{1}$$

Whereas $\bar{x}_i(t) = [x_i(t), y_i(t), \psi_i(t)]^T$. n_{UAV} defines the number of UAVs. x, and y denotes the position along the axes, ψ denotes the heading angle and u represents the control input vector. The time step is represented by t and i denotes that the variables belong to i^{th} UAV. Fig. 1 shows the kinematics geometry of UAV in which a signifies the acceleration and v represents the velocity. The kinematics of UAV related to the inertial frame can be written as

$$\begin{cases} \dot{x}_i(t) = v_i.sin(\psi_i(t)) \\ \dot{y}_i(t) = v_i.cos(\psi_i(t)) \\ \dot{\psi}_i(t) = \frac{a_i(t)}{v_i} \\ \dot{u}_i(t) = a_i(t) \end{cases} \tag{2}$$

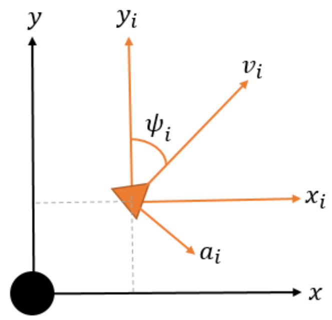

Fig 1: Kinematics of UAV

From equations (1), $\bar{x}_i(t+1)$ can be rewritten as

$$\bar{x}_i(t+1) = \begin{bmatrix} x_i(t) \\ y_i(t) \\ \psi_i(t) \end{bmatrix} + \begin{bmatrix} v_i.sin(\psi_i(t)) \\ v_i.cos(\psi_i(t) \\ \frac{a_i(t)}{v_i} \end{bmatrix} .\Delta E \tag{3}$$

The UAV's motion can be inhibited by the maximum and minimum velocities ($v_{minimum} \leq v_i \leq v_{maximum}$), the minimum radius ($r_{minimum}$), and maximum control input which can be represented as ($u_{maximum} = \frac{v^2}{r_{minimum}}$).

B. Target Model

The dynamics of the target have been defined in Fig. 2 and the target will be demonstrated as a point mass. Consider the altitude of point zero. The state vector at the time step t can be written as

$$\bar{x}_E(t) = [\bar{T}_E(t), \bar{v}_E(t)]^T \tag{4}$$

Whereas $\bar{T}_E(t) = (T_{E_x}(t), T_{E_y}(t))$ and $\bar{v}_E(t) = (v_{E_x}(t), v_{E_y}(t))$. E signifies the target variables, $\bar{T}_E(t)$ denotes the position and $\bar{v}_E(t)$ represents the target velocity vectors. Similarly, subscript x and y represent the projections.

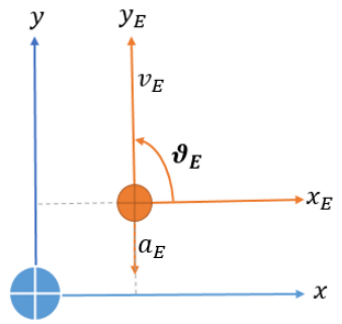

Fig 2. Dynamics of target

The target dynamics measured is specified by

$$\bar{x}_E(t+1) = \dot{\bar{x}}_E(t)\Delta k + \bar{x}_E(t) \tag{5}$$

Whereas Δk denotes the sampling time. The ground vehicle dynamics can be inhibited by the turning maximum velocity ($V_{maximum}$) and minimum turning radius ($r^E_{minimum}$). The angle $\vartheta_E(t)$ among the velocity vector and x-axis can be attained by the following equation.

$$\vartheta_E(t) = tan^{-1}\left(\frac{v_{E_y}(k)}{v_{E_x}(k)}\right) \tag{6}$$

The course vector indicates the direction where the target is moving. Therefore the values of the angles are $\vartheta_E(t) = 0$, $\vartheta_E(t) = \frac{\pi}{2}$, $\vartheta_E(t) = \pi$ and $\vartheta_E(t) = \frac{3\pi}{2}$ in east, north, west, and south simultaneously.

C. *Sensor coverage region (SCR)*

In the mission of target tracking, the target point should be within the coverage region of the sensor. The body-fixed sensor is usually installed on the UAVs. It will compensate for the change in observation angle attained by the variation in the attitude of the vehicle. So, the coverage region will also be circular. However, a body-fixed sensor with the variation in attitude, the region also changes which leads to more complications. This section defines these above-mentioned issues and the model of sensor coverage. Fig.3 (a-b) shows the coverage region of the sensor in straight and turning flights concurrently.

In Fig.3 (a), UAV is flying in a straight flight and the SCR will be circular and the center axes equal the position of the UAV. The radius $r = c.tan\alpha$ whereas α denotes the field angle of the sensor. Similarly, in Fig.3 (b) UAV is flying in a rotating flight and the SCR will be elliptic attaining angle β which signifies the roll angle. The center of the coverage region can be written as

$$x_{O-n} = \frac{1}{2}c[tan(\alpha+\beta) - tan(\alpha-\beta)] + x_{uav} \tag{7}$$

$$y_{O-n} = y_{uav} \tag{8}$$

The long and short axes are denoted by (l, m) of the elliptic area and can be expressed as

$$l = \frac{1}{2}c[tan(\alpha+\beta) - tan(\alpha-\beta)] \tag{9}$$

$$m = c.tan\alpha \tag{10}$$

The coordinates in an inertial frame (x, y) can be transmuted to (x_n, y_n) as follows

$$\begin{bmatrix} x_n \\ y_n \end{bmatrix} = \begin{bmatrix} c\psi & s\psi \\ -s\psi & c\psi \end{bmatrix} \begin{bmatrix} x - x_{O-n} \\ y - y_{O-n} \end{bmatrix} \tag{11}$$

Whereas c denotes cos and s denotes sin. The SCR in x_{O-n} and y_{O-n} can be written as

$$R_{SCR} = \left[(x_n, y_n)\left|\frac{x_n^2}{l^2} + \frac{y_n^2}{m^2}\right.\right] \tag{12}$$

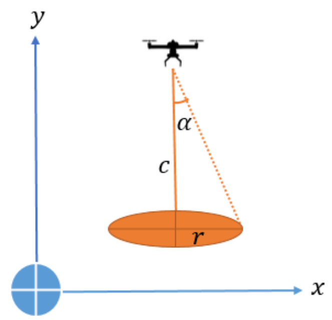

Fig 3 (a). SCR in a straight flight

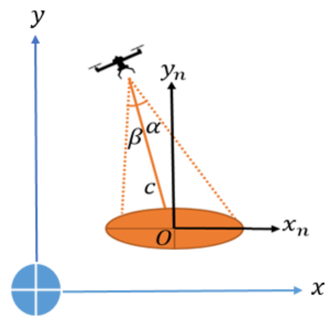

Fig 3 (b). SCR in a rotating flight

D. *Restricted region*

Obstacles vary in size which helps in building the restricted region [24-25]. For the safety of the flight, UAVs must avoid these obstacles. Usually, the obstacles like building with circular or rectangular areas attaining height c are considered restricted areas. Consider the tall obstacles/buildings W attaining the origin O_h whereas $h = [1, \ldots, W]$. The distance among the UAV and boundary of an obstacle is denoted by D_{x-O_h}. The distance is zero when the plane (x, y) falls inside of the obstacle. Finally, the restricted region can be

$$H^c = \{(x, y)\epsilon S^2 | D_{x-O_h} \leq 0\} \tag{13}$$

E. *Space limitation between UAVs*

The UAVs usually collide with each other when they are very close. Therefore, the distance between them should be larger than the innocuous distance i.e. ($D_{minimum}$). During the flight, communication takes place between UAVs to exchange information. Thus, the distance among them should not be larger than ($D_{maximum}$). Fig. 4 shows the spacing limitation where P_1 and P_2 are the paths. It can be modeled as $D_{minimum} \leq D \leq D_{maximum}$.

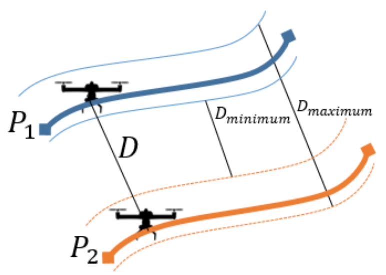

Fig 4. Space limitation between UAVs

V. Improved Grey Wolf Optimizer (IGWO)

The GWO method is a very intelligent and efficient optimization algorithm. It attains good stability, accuracy, and search capability. It also applies to many engineering problems to solve various issues. But in GWO, an untimely convergence problem is still present. Thus, this manuscript presents a new method namely Improved Grey Wolf Optimizer (IGWO) with some improvement strategies.

A. Grey Wolf Optimizer (GWO) method

Wolfs are considered extroverted animals with helpful work and group hierarchy. The four positions of grey wolf population from high to low are Lambda (λ), Mu (μ), Xi (ξ), and Rho (ρ). Frequently, the higher grade provides instructions for the lower grade. This higher-grade also asserts the recommendation of a lower grade. In these above-mentioned positions, λ is considered as the best first solution. Similarly, μ and ξ are both considered as the second and third solutions respectively. ρ signifies all other solutions. The three main process phases of a grey wolf are as follows

- Target will be outlined by the package of the wolf.
- The package of the wolf environs the target.
- The package of the wolf reaches the target.

This strategy or phase is considered the best solution. Consider wolfs $\mathcal{W}$ in the population $Q_{\mathcal{W}} = [Q_1, \ldots, Q_{\mathcal{W}}, Q_{w}]$. The position of the wolf is $Q_{\mathcal{W}} = [Q_{\mathcal{W}}^1, \ldots, Q_{\mathcal{W}}^p, Q_{w}^{\partial}]$ whereas the Q_{w}^p is the p-dimensional position of the wolf. The following equation is used to model the grasping process.

$$Q_{\mathcal{W}}^p(t+1) = Q_d^p(t) - K_{\mathcal{W}}^p \left| L_{\mathcal{W}}^p . Q_d^p(t) - Q_{\mathcal{W}}^p(t) \right. \quad (14)$$

Whereas Q_d^p denotes the target position, t denotes the iteration. The size of the clinch is $K_{\mathcal{W}}^p \left| L_{\mathcal{W}}^p . Q_d^p(t) - Q_{\mathcal{W}}^p(t) \right.$.

$$K_{\mathcal{W}}^p = 2F.rand - F \quad (15)$$
$$L_{\mathcal{W}}^p = 2.rand \quad (16)$$

Whereas $rand$ signifies the values range from 0 to 1. The variable F decreases with the steps of iteration from 2 to 0.

$$F = 2 - \frac{t}{t_{maximum}} \quad (17)$$

Whereas $t_{maximum}$ denotes the maximum iteration. Equations (14-17) ensure the confined search and exploration i.e. global search. Now, during the process, the target position Q_d becomes the optimization issue i.e. the preferred position optimization issue. Still, the solution is unidentified throughout the optimization process. The position of the wolf Q_λ, Q_μ and Q_ξ must be closer to the target position. The position of the target can be restructured based on the following three positions that are as follows.

$$\begin{cases} Q_{\mathcal{W},\lambda}^p(t+1) = Q_\lambda^p(t) - K_{\mathcal{W},\lambda}^p \left| L_{\mathcal{W},\lambda}^p . Q_\lambda^p(t) - Q_{\mathcal{W}}^p(t) \right. \\ Q_{\mathcal{W},\mu}^p(t+1) = Q_\mu^p(t) - K_{\mathcal{W},\mu}^p \left| L_{\mathcal{W},\mu}^p . Q_\mu^p(t) - Q_{\mathcal{W}}^p(t) \right. \\ Q_{\mathcal{W},\xi}^p(t+1) = Q_\xi^p(t) - K_{\mathcal{W},\xi}^p \left| L_{\mathcal{W},\xi}^p . Q_\xi^p(t) - Q_{\mathcal{W}}^p(t) \right. \end{cases} \quad (18)$$

$$Q_{\mathcal{W}}^p(t+1) = 0.3 \times \sum_{e=\lambda,\mu,\xi} Q_{\mathcal{W},e}^p(t+1) \quad (19)$$

B. Improved Grey Wolf Optimizer (IGWO) method

Social learning and group communication lead to the best possible solution in the GWO method. But, the experience of each wolf is neglected. Thus, only the globally finest position is deliberated. The separate memory is now summed into equation (20) as follows

$$Q_{\mathcal{W}}^p(t+1) = j_1.0.3 \times \sum_{e=\lambda,\mu,\xi} Q_{\mathcal{W},e}^p(t+1) + j_2.rand.(Q_{\mathcal{W},finest}^p - Q_{\mathcal{W}}^p(t)) \quad (20)$$

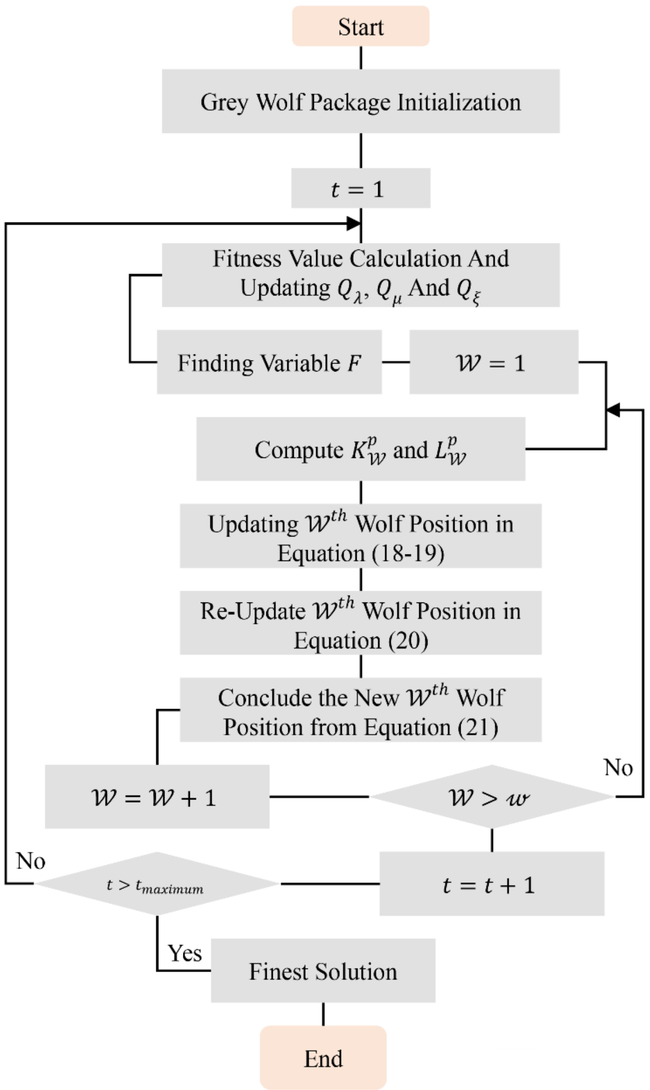

Fig 5. IGWO process

Whereas j_1 and j_2 denotes the learning factors of societal learning and separate memory simultaneously. $rand$ is the random value from 0 to 1. $Q_{\mathcal{W},finest}^p$ signifies the finest solution of the grey wolf. Now, the opinion of survival fittest is applied with probability P. The tactic can be expressed as

$$Q_{\mathcal{W}}(t+1) = \begin{cases} Q_{\mathcal{W}}(t+1) & e(Q_{\mathcal{W},new}(t+1)) > e(Q_{\mathcal{W}}(t)),\ rand < d \\ Q_{\mathcal{W},new}(t+1) & otherwise \end{cases} \quad (21)$$

The last iteration position is $Q_W(t)$. Similarly, $Q_{W,new}(t+1)$ denotes the new position. $rand$ denotes the random value from 0 to 1. This tactic results in the finest solution. Fig. 5 shows the IGWO process flow diagram.

VI. Simulation Results

The simulations were carried out in MATLAB software. The time requires in the simulation process is 240 $seconds$ and the execution time is 1.3 $seconds$. The area attains the size 100 $meters$ × 1200 $meters$ with obstacles of different sizes and shapes. Consider a scenario in which three UAVs target the points with different motions. All vehicles achieve the same height approximately 290 $meters$. The initial positions of a vehicle are (0,100), (0,120), and (180,0) in meters simultaneously. The heading angle of each vehicle is 40° and a velocity is considered as 28 m/s. Similarly, the acceleration is 3 m/s^2 and the roll angle is 30°. The minimum and maximum distance is 40 $meters$ and 550 $meters$ simultaneously. The table below defines the parameters of IGWO.

Table I: IGWO Parameters

w	**32**
∂	30
$t_{maximum}$	180
j_1	0.5
j_2	0.3
d	0.7

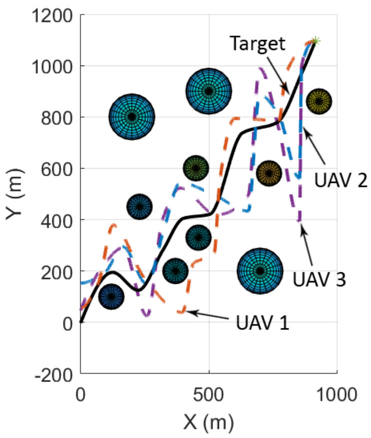

Fig 6 (a). Trajectories in a 2D plane

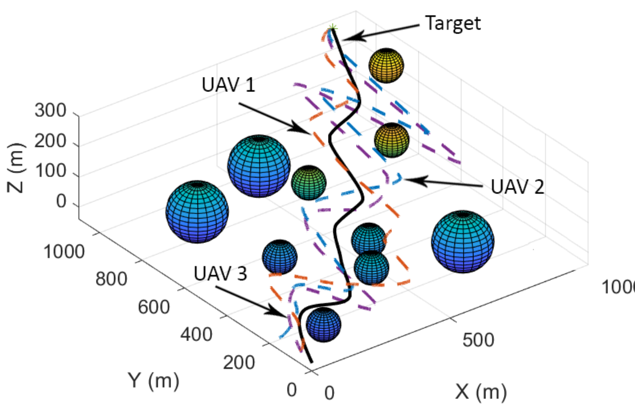

Fig. 6(b). Trajectories in a 3D plane

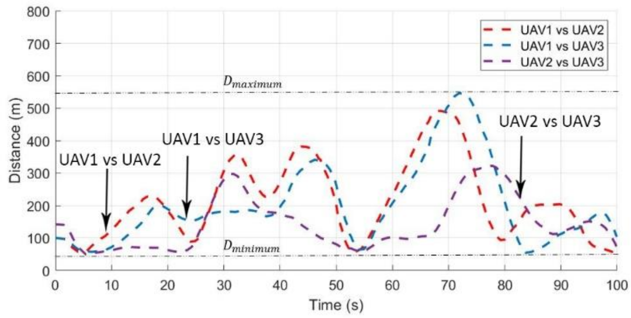

Fig 7. UAVs distance

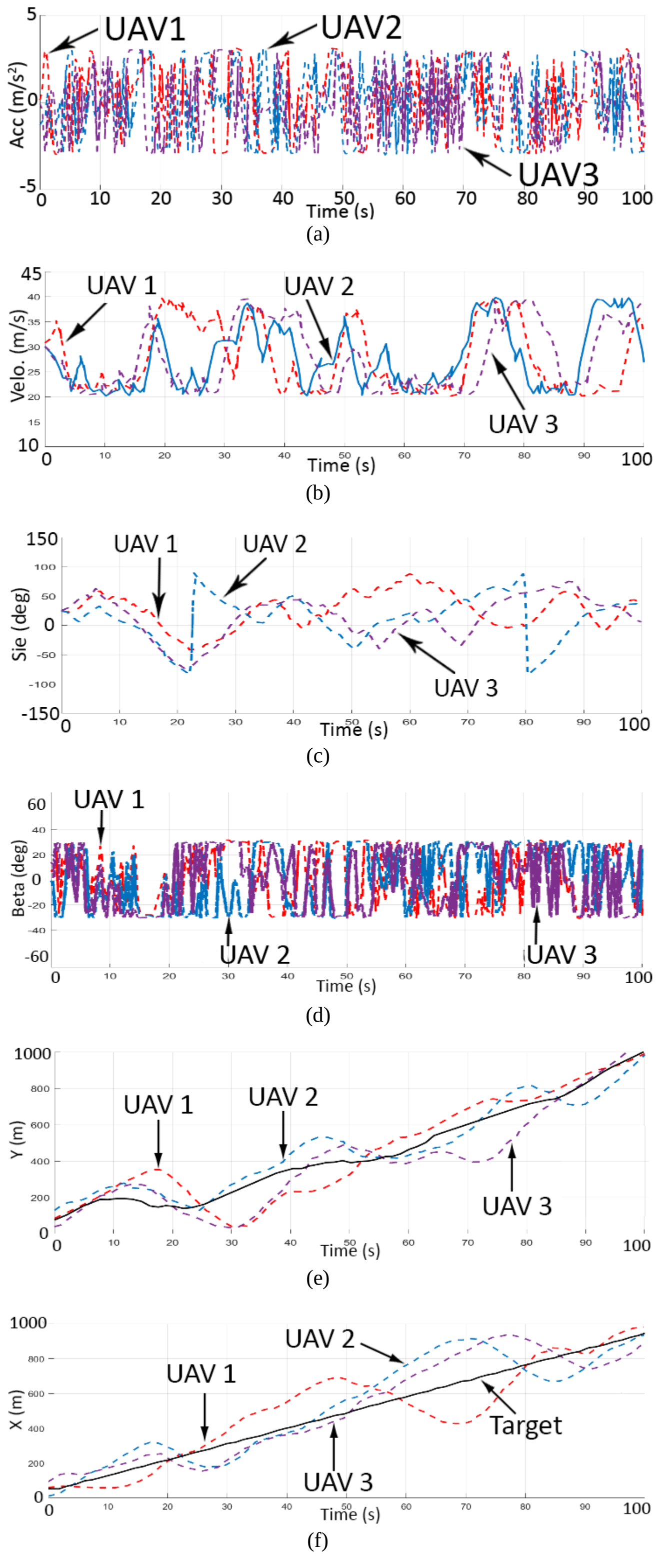

Fig 8 (a-f). Control inputs and State variables

Fig. (6-8) shows the tracking process of UAVs by using the algorithm IGWO. In Fig. 6(a-b), three UAVs avoid the hurdles and obstacles and reach the targeted position. Fig. 7 shows the distance between the UAVs which fulfills the space limitations. It means that the communication among vehicles will remain kept without any collision. Furthermore, Fig. 8(a-f) shows the control inputs and state variables. Finally, the designed approach attains excellent performance in tracking.

VII. Conclusion

This manuscript defines the multiple UAVs tracking for moving ground targets by using the Improved Grey Golf Optimizer (IGWO) technique. The proposed scheme solves the trajectory optimization problems with its strong ability and performance. This study also considers the dynamic constraints of UAVs along with the requirements of the mission. It presents the target model with the sensor coverage region. The IGWO attains higher searchability, efficiency, stability than basic GWO. The simulations results validate that the proposed scheme achieves higher performance in tracking multiple UAVs with higher robustness and security.

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