NOVEL NATURE-INSPIRED AUTONOMOUS GUIDANCE OF AERIAL ROBOTS FORMATION REGARDING HONEY BEE ARTIFICIAL ALGORITHM AND FUZZY LOGIC

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In this article, a novel nature-inspired autonomous guidance is investigated regarding the honey bee motion algorithm for aerial robots and fuzzy logic. Combination of the bee algorithm and fuzzy logic is proposed to achieve an on-line guidance for methodology of this research. The main idea of this work belongs to a novel analogy between honey bees and aerial robots motions. Moreover, information links between the aerial robots are demonstrated to construct a formation of vehicles by updating motions based on fuzzy decision making. Three dimensional simulations for the aerial robots are considered to show the efficient performance of autonomous guidance. The simulation results show precise ability of the proposed method for aerospace and robotics engineers based on a nature phenomenon to present an innovative guidance method.

Keywords: nature-inspired guidance, honey bee swarm, optimal trajectory, aerial robots, fuzzy logic

1. Introduction

Autonomous aerial robots with on-line guidance are appealed for use in civil missions. Conventional sophisticated guidance methods require new researches and ideas to develop next generation aerial robots. Usual off-line guidance methods are based on ground station. Therefore, reducing ground station commands by novel intelligent methods is necessary for further development of aerial robots. Thus, self-contained on-board guidance regarding novel methods have been considered (Ma *et al.*, 2006; Eng *et al.*, 2010; Babaei *et al.*, 2011; Paw and Balas, 2011; Al-Rabayah and Malaney, 2012; Bitam *et al.*, 2013; Samani *et al.*, 2015).

Mavrovouniotis *et al.* (2017) focused on investigation of changes in dynamics of swarm intelligent algorithms and comparing of them to increase their performance. Mettler *et al.* (2010) studied autonomous guidance with respect to receding horizon optimization. The main system was integrated based on the cost function approximation regarding optimal path planning. An account of engineering applications of swarm intelligent optimization algorithms were represented by Rajasekhar *et al.* (2017). Also, some real engineering applications with the honey bees optimization method were illustrated in (Rajasekhar *et al.*, 2017). Laomettachit *et al.* (2015) investigated bifurcation analysis and stochastic simulations in honey bee swarms regarding adaptive decisions making. Moreover, Luo *et al.* (2019) represented the swarm intelligent algorithm as MSA. It is a new elite opposition-based that named as MSA. Furthermore, Zedadra *et al.* (2018) discussed about a decentralized system like honey bees algorithms. Also, other advantages such as self-organization, ability to overcome sophisticated problems regarding incomplete information and limitation in computation were investigated. Moreover, other advantages with respect to Internet of Things (IoT)'s application were investigated by Zedadra *et al.* (2018). Furthermore, Zhou *et al.* (2019) researched on autonomous guidance aerial vehicles with more

dimensional spaces and different cost functions. In this way, Zhou *et al.* (2019) studied a hierarchical algorithm by learning different tasks.

In (Huang *et al.*, 2016), a k-degree smoothing for trajectory design was proposed regarding complex environment for multiple threat sources. In (Liu *et al.*, 2016), artificial intelligence and particle swarm optimization were considered in combination with an adaptive sensitivity algorithm for optimal trajectory. In (Chen *et al.*, 2017), an encoding approach with respect to the two-part wolf pack search algorithm was proposed for multiple autonomous aerial robots to obstacle avoidance of complex environment. Moreover, algorithms as genetic, swarm of birds, random search and firefly were comprised in the same conditions. Results in (Chen *et al.*, 2016) illustrated that more autonomous guidance methods had precise performance for real dynamic models of aerial robots. Furthermore, on-line sweep calculation was proposed for trajectory optimization of aerial robots for three dimensional terrain reconstruction (Torres *et al.*, 2016).

In this work, a novel guidance is presented based on the analogy between optimal honey bees motion and aerial robots. A novel analogy is described and three dimensional simulations are demonstrated. Next, the integrated by fuzzy logic guidance and information linkages for aerial robots are investigated. The results show the ability of the proposed guidance for autonomous aerial robots.

2. Novel guidance for autonomous aerial robots

Food sources (flowers nectar) and bees are two main parts of honey bees swarm motion. In our approach, bees are considered as aerial robots and food sources as artificial targets. The main target is considered as one of the artificial targets. An initial population for different artificial targets is considered randomly. The search space (main domain) is defined by minimum and maximum of bounds where the main target is placed in this domain. So, three bounds are considered as

$$\overline{X} = \{X_{min}, X_{max}\} \qquad \overline{Y} = \{Y_{min}, Y_{max}\} \qquad \overline{Z} = \{Z_{min}, Z_{max}\} \tag{2.1}$$

A place in the above $[\overline{X}, \overline{Y}, \overline{Z}]$ cubic domain is taken as the main target.

Aerial robots are considered in three types like bees in Artificial Bee Colony algorithm (ABC). Worker, onlooker and scout bees are named as types of A, B and C, respectively. Aerial A-type robots have initial random roles. In this algorithm, A-type aerial robots positions are distributed in the main domain $[\overline{X}, \overline{Y}, \overline{Z}]$ randomly like in reality. The mentioned distribution is named the zero positions (X_0, Y_0, Z_0). Next, the aerial robots from (X_0, Y_0, Z_0) move to the next positions (X_i^*, Y_i^*, Z_i^*). These movements are like the first iteration in the optimization algorithm of ABC. Index i belongs to the number of aerial robots. Moreover, the bounds of the search space are determined as ε_x, ε_y, ε_z

$$|X_{max} - X_{min}| = \varepsilon_x \qquad |Y_{max} - Y_{min}| = \varepsilon_y \qquad |Z_{max} - Z_{min}| = \varepsilon_z \tag{2.2}$$

Furthermore, X^*, Y^*, Z^* are derived based pn the following equations

$$
\begin{aligned}
X_i^* &= \frac{|X_{max}| + |X_{min}|}{2} + \left(|rand| \leqslant \left|\frac{\varepsilon_x}{2}\right|\right) \\
Y_i^* &= \frac{|Y_{max}| + |Y_{min}|}{2} + \left(|rand| \leqslant \left|\frac{\varepsilon_y}{2}\right|\right) \\
Z_i^* &= \frac{|Z_{max}| + |Z_{min}|}{2} + \left(|rand| \leqslant \left|\frac{\varepsilon_z}{2}\right|\right)
\end{aligned}
\tag{2.3}
$$

In the above equations, $|rand|$ demonstrates a random number smaller than $ve_k/2$ ($k = x, y, z$). In this way,X_i^*, Y_i^*, Z_i^* demonstrate the next position of the i-th aerial robot in the cubic domain

(see Figs. 1a and 1b). According to the ABC, second positions of aerial vehicles are achieved randomly.
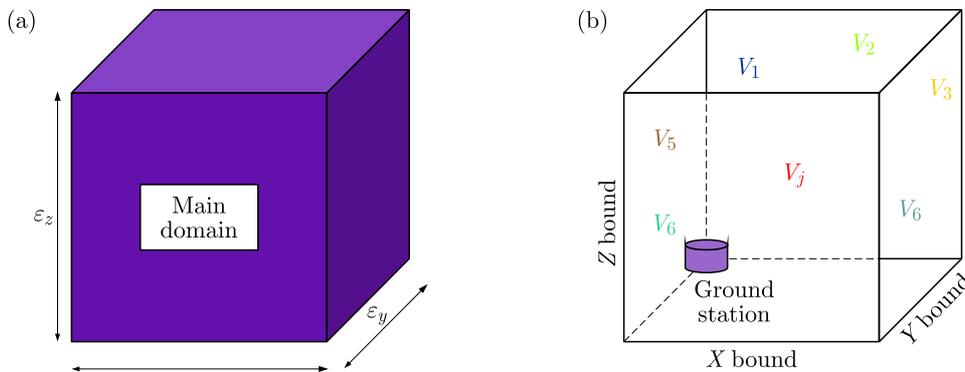

Fig. 1. (a) Three dimensional bounds/cubic domain, (b) random positions of aerial robots in the cubic domain

A flowchart of the proposed nature-inspired guidance is illustrated in Fig. 2.
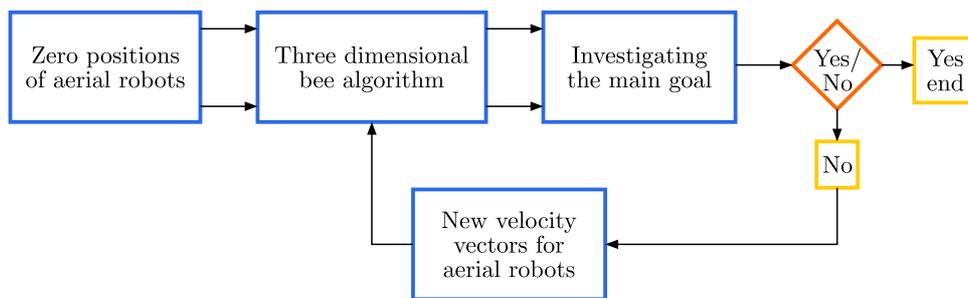

Fig. 2. Flowchart of novel proposed guidance based on the bee algorithm

A-type aerial robots search for artificial targets, which memorize the positions of targets. Next, the new artificial targets are updated and shared with B-type aerial robots. B-type aerial robots search for the closest artificial targets based on the length of distances. The third role of aerial robots belongs to the C-type when an artificial target is not improved after a limited number of searches. Therefore, C-types aerial robots help to achieve better targets and replace the last artificial targets. Hence, C-types aerial robots improve the algorithm to find the best artificial target in the defined domain. Also, for each artificial target, A-types generate new motion to search the next artificial targets and their neighborhood

$$ {}^m\bar{\zeta}_n^j = {}^m\zeta_n^j + \sigma_n^j({}^m\zeta_n^j - {}^m\zeta_k^j) \tag{2.4} $$

where $m \in \{x, y, z\}$ directions, $j \in \{1, 2, 3, \ldots, N\}$, N is the number of aerial robots. k index denotes the random neighbor target that may help updating artificial targets, and n demonstrates the iteration in the mentioned algorithm. and $k = n - 1$. Also, σ_n^j is a random value ranging in $[-1, 1]$ that causes random motions.

One of the most important phenomenon in the characteristics of bees is nutation dancing. When A-type aerial robots return to hive, aerial robots send a nutation signal. When A-type aerial robots return to hive by their nutation signals, they transform the information of artificial

targets to B-type aerial robots. Then, the selection of a target by B-type aerial robots is denoted by P_n

$$P_n = \frac{\text{fit}_n}{\sum\limits_{m=1}^{N} \text{fit}_m} \tag{2.5}$$

The qualities of the artificial targets are demonstrated by fit_n. Also, aerial robots can transfer their information. Aerial robots with more fuel will be remained. Finally, there may be some artificial targets that cannot be searched by A and B-types. Hence, based on tuning parameters of the algorithm μ, C-types aerial robots are sent to search in the main domain. C-type aerial robots help the algorithm to find not searched artificial targets. It means that this algorithm can overcome difficulties of finding the global/main target. It is one of the advantages of this algorithm that is used as novel guidance for aerial robots.

To summarize the main idea of the mentioned guidance, one can categorize it in 8 steps.

1) The first step belongs to initial motion of aerial robots. It should be noted that this step is completely random in the defined domain.
2) Distances from artificial targets are evaluated.
3) The stop criterion may occur or a new distribution is formed. In this step, formation of aerial robots occurrs while the stopping criterion (finding the main target) is met.
4) Neighborhood search is investigated to find the minimum distance from artificial targets.
5) Recruitment aerial robots for selected artificial targets are considered and distances are evaluated again.
6) The main target is selected based on distances of aerial robots.
7) To increase the ability of the mentioned algorithm, the remaining aerial robots are assigned to search randomly. Their distances are evaluated by other aerial robots.
8) Finally, the algorithm stops as considered in step 3. Therefore, the algorithm is completed.

3. Simulation by point mass dynamic of motion

Dynamical system equations for motions of aerial robots are given in (3.1). Through them the routes can be obtained

$$\frac{dx_i}{dt} = V_i \cos \varphi_i \cos \psi_i \qquad \frac{dy_i}{dt} = V_i \cos \varphi_i \sin \psi_i \qquad \frac{dz_i}{dt} = V_i \sin \varphi_i \tag{3.1}$$

where V_i is the total velocity, the index i is referred to the number of aerial robots of the missions, φ, ψ are angles of velocity vectors.

Based on the above description, Figs. 3 and 4 show the initial random distribution in the defined domain and the formation of aerial robots in the first iteration respectively.

Also, in Fig. 5a, one can see the second motion of aerial robots, and they do not converge in the second iteration. However, Fig. 5b demonstrates final iterations of the algorithm and how the robots converge to the main target $(0, 0, 0)$.

Also, positions of C-type aerial robots are shown in Fig. 6a. In Fig. 6b, the path of one of A-type aerial robots is sketched.

4. Integrated proposed guidance by fuzzy

In this part, autonomous guidance for aerial robots is improved by an intelligent method as fuzzy logic. Fuzzy logic can use linguistic statements and it is a wistful method in the guidance.
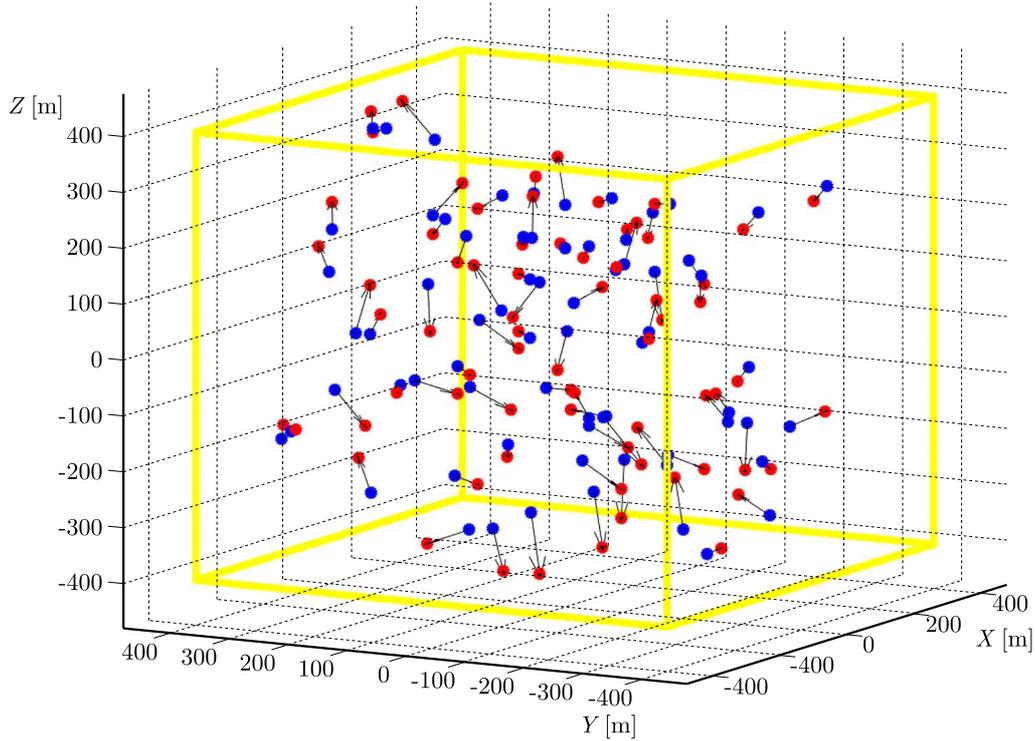
Fig. 3. Three dimensional random initial motion of aerial robots, 20 aerial robots
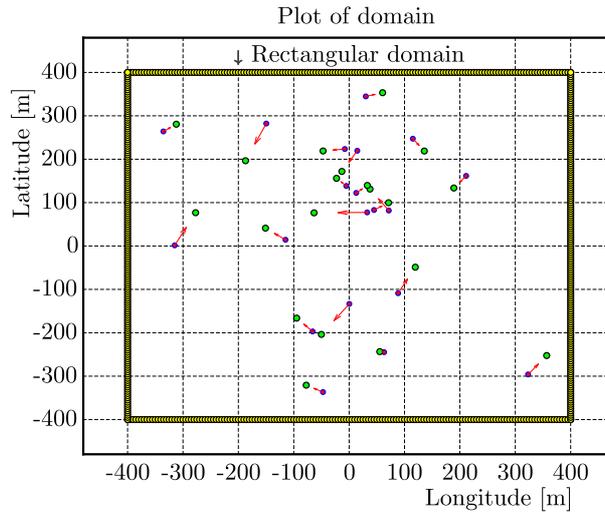

Fig. 4. Convergence procedure of aerial robots in middle iterations of the algorithm, main target in $(0, 0, 0)$, 200 aerial robots

Moreover, graphs are used to develop information linkages between aerial robots. Each aerial robot has information relationships between them. Information relationship linkages can transfer the information of aerial robots. The linkages are denoted by $\alpha\mathbf{l}$, where α is a design coefficient $\alpha \in [0, 1]$ and $\mathbf{l}$ is a vector that has information on aerial robots. $\mathbf{l}$ can be a function of position $\mathbf{R}$ where $\mathbf{R} = [x, y, z]$, quality of information is $\mathbf{\Omega}$ and distance from the destination is $\Im$. Therefore, the information linkages can be denoted as $\mathbf{l} = \mathbf{l}(\mathbf{R}, \mathbf{\Omega}, \Im)$ where $\mathbf{R}$, $\mathbf{\Omega}$, $\Im$ are described. It should be noted $\mathbf{\Omega}$ can be a function of the received information from GPS and distance to the destination $\Im$ implicitly. There are many $\mathbf{l}$ linkages between aerial robots. Next, based on $\mathbf{l}_{sr}$ between the aerial robot (s) and the aerial robot (r), the fuzzy rules are constructed to guide
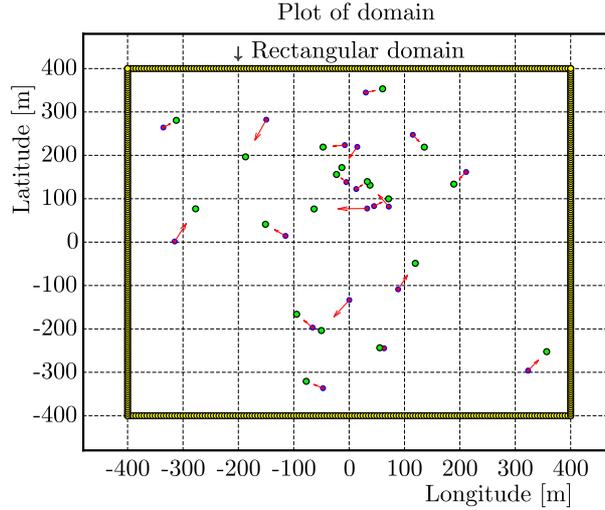
Fig. 5. Random initial motion of aerial robots (a) in middle iterations and (b) for final iterations of the algorithm, main target $(0,0,0)$, 200 aerial robots
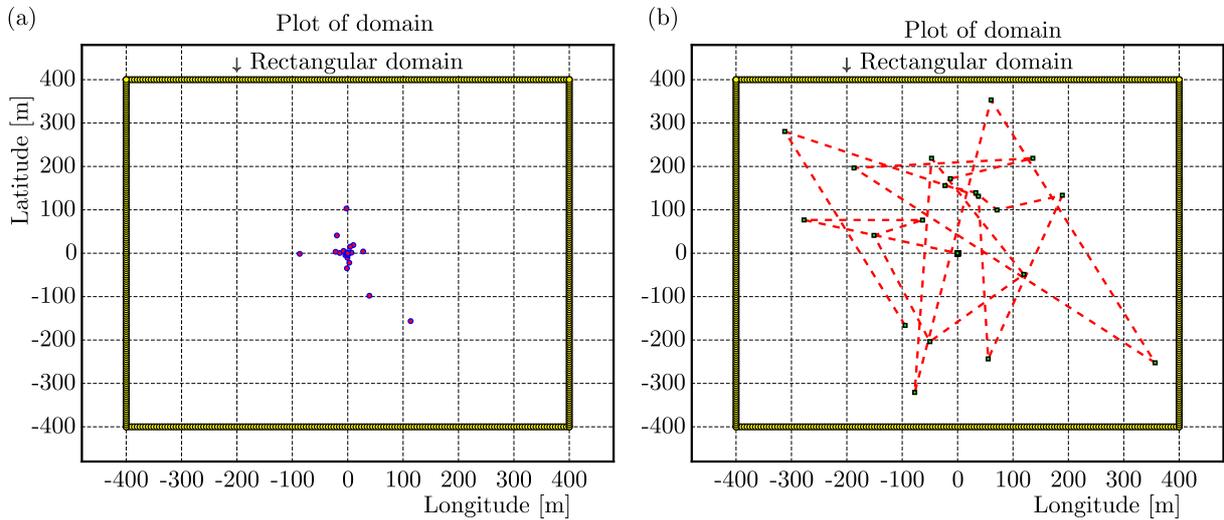

Fig. 6. (a) One of the paths of A-type aerial robots. (b) Investigating C-type aerial robots for 20 C-type aerial robots

the aerial robots intelligently to increase the quality of the previously proposed guidance. In this way, $\mathbf{l}_{sr}$ can be formulated as below

$$\mathbf{l}_{sr}^{P} = |\boldsymbol{\varsigma}(s) - \boldsymbol{\varsigma}(s+1)|_{r=s+1} \tag{4.1}$$

where $\boldsymbol{\varsigma}(\cdot)$ is the vector of position of aerial robots. Also, the indices s and $s+1$ are considered because the aerial robots s and $s+1$ are close to each other, therefore they have better information transfer.

Furthermore, $\mathbf{l}'_{sr}$ is considered as

$$\mathbf{l}'^{P}_{sr} = |\boldsymbol{\varsigma}(s) - \boldsymbol{\varsigma}(e)|_{e=random} \tag{4.2}$$

The information linkage between the aerial robots s and other aerial robots is considered as a random aerial robot position. In this way, all transform linkages can be evaluated. It should be noted that position of the above is the vector direction x, y and z. Therefore, components of the linkages are constructed based on two vectors and one constant $\mathbf{l}'_{sr}$ or $\mathbf{l}_{sr} = \mathbf{l}(\mathbf{R}, \boldsymbol{\Omega}, \Im)$. Information about the position of aerial robots is achieved from GPS and the vector of position.

The main problem of this part is how $\mathbf{l}_{sr}$ or $\mathbf{l}'_{sr}$ are used in the proposed guidance. The answer to this problem is fuzzy logic. Based on the predefined fuzzy rules, decisions for the aerial robots are made and help the previous algorithm to increase its operation to yield more qualified results with more precession.

The above method is considered for A-type aerial robots. Therefore, the formation flight guidance of aerial robots is developed based on the receiving data from GPS and fuzzy logic decisions. Hence, some rules for fuzzy logic are illustrated as below:

1. *If there is no GPS signal* then *high usual behavior of the algorithm is considered.*
2. If *GPS signal is low* then *high usual behavior of the algorithm is considered.*
3. If *GPS signal is high* then *low usual behavior of the algorithm is considered.*
4. If *there are no* $\mathbf{l}_{sr}$ *or* $\mathbf{l}'_{sr}$ *signals* then *usual behavior of the algorithm is considered.*
5. If $\mathbf{l}_{sr}$ *or* $\mathbf{l}'_{sr}$ *signals are high* then *low usual behavior of the algorithm is considered.*
6. If $\mathbf{l}_{sr}$ *is high and* $\mathbf{l}'_{sr}$ *is low* then *medium behavior of the algorithm is considered.*
7. If $\mathbf{l}_{sr}$ *is high and* $\mathbf{l}'_{sr}$ *is high* then *low behavior of the algorithm is considered.*
8. If $\mathbf{l}_{sr}$ *is low and* $\mathbf{l}'_{sr}$ *is low* then *high behavior of the algorithm is considered.*

The above demonstrated some fuzzy rules considered in this work. It is concluded the nature--inspired guidance illustrated in Section 3 can be improved by an intelligent method like fuzzy logic. Therefore, integrated nature-inspired guidance and fuzzy logic will have more precise results. Comparison of the two proposed guidance methods to show high accuracy of an integrated nature-inspired guidance against only a nature-inspired guidance algorithm is demonstrated in Table 1.

Table 1. Comparison of two proposed guidance algorithms

	Nature-inspired guidance	Integrated nature-inspired guidance
Total path for all aerial vehicles (50 vehicles)	8536 m	6432 m
Total time for all aerial vehicles (50 vehicles)	32 s	25 s

5. Conclusion

This study focuses on considering a nature-inspired autonomous guidance algorithm for multiple aerial robots. However, not only the main idea of this algorithm is considered as a novel nature--based autonomous guidance but also it is considered as a novel guidance method which is naturally optimal for aerial robots in three dimensional space. Moreover, one of the important outcomes of this research is an integrated bee algorithm and an intelligent method as fuzzy logic to increase the ability of aerial robots in terms of autonomous guidance. Finally, the autonomous characteristic is the most important advantage of nature-inspired and integrated nature-inspired guidance algorithms. The autonomous behavior of aerial robots has high worthiness for aerospace engineers. Therefore, autonomous aerial robots will be designed intelligently with the novel combination of the ABC algorithm and fuzzy logic.

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