Research on Multi-UAV Swarm Control Based on Olfati-Saber Algorithm with Variable Speed Virtual Leader

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Abstract. The high efficiency of control between multiple drones has become a hot topic of research nowadays. Due to the increased demand for combat operations and the increasing number of drones, the efficiency of control between multiple drones has become a hot research topic. Drawing on the principles of some communication in swarm intelligence, it is of great significance for realizing the autonomous cooperative control between UAVs. Learning from the Olfati-Saber algorithm, this paper proposes an optimized algorithm with virtual leaders, in order to make the group speed converge faster and more stable. Then, this paper also shows the impact of variable-speed virtual leaders on complex drone communication systems. Subsequently, two models are simply analyzed and compared with each other in the article. Through the simulation, we prove the effectiveness of certain variable speed virtual leaders for decentralized clusters of complex UAV systems, which improves the application of Olfati-Saber model in practice.

Keywords: Complex UAV network · Variable speed virtual leaders · Swarm intelligence

1 Introduction

Collection Intelligence refers to a group of animals living in groups in nature, which are intelligent behaviors in daily life and actions that are affected by communication between individuals and affect group traits. In nature, bee swarms, ant swarms, wild wolf swarms, bird swarms, geese swarms, fish swarms, etc. are all similar to this rely on the communication between individuals through the layer-by-layer transmission, and thus affect the direction of the entire group, and maintain the formation of the entire group. Once encountering special circumstances, such as obstacles, or natural enemies and other situations that require a change of direction, they can still keep all individuals of the entire group moving forward at a common speed and a common formation.

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Flocking is used to describe this kind of phenomenon that can quickly affect the group through the exchange of information between a small number of individuals without knowing the status of the group. At the same time, the exchange of information between a few individuals, the strong resistance to environmental noise, and the rapid transformation of group behavior is also an indispensable part of the swarming behavior. Such a magical natural phenomenon has attracted a lot of interest from scholars all over the world. Scholars in biology, computer, physics and other fields have conducted modeling and simulation research in this field, which has further promoted the richness of swarm intelligence algorithms [1, 2].

In 2006, Olfati-Saber innovatively proposed three algorithms. Saber's first algorithm was designed with reference to the three principles in the Boid model, but it does not guarantee that every individual in the group can form a bee colony and move forward together. Saber's second algorithm proposes a swarming algorithm with virtual leaders, which solves the problem of poor clustering effect and the inability to form a stable bee colony in the past. Saber's third algorithm is based on the second algorithm, and more practically considers the situation that contains obstacles, and realizes the intelligent obstacle avoidance of the bee colony in the simulation algorithm [3]. The Saber algorithm provides a profound reference value for many subsequent scholars to study swarm intelligence, and promotes the progress of algorithms in the field of swarm intelligence [4–12].

The structure of this article is summarized as follows: The first chapter introduces the background and source of the subject. Section 2 introduces the system model of swarm intelligence. Section 3 presents the Olfati-Saber second algorithm model. At the same time, the formation of a virtual leader with variable speed was also proposed. By comparing the different results of several simulations, the advantages and disadvantages of the variable speed virtual leader are analyzed in Sect. 4. Finally reached the conclusion of this article.

2 Multi-agent-Aware Network Model

Drawing on the knowledge of graph theory, we define the graph $G(t) = \{v,\varepsilon(t), A(t)\}$ in the algorithm by the vertex set $V = \{v_1, v_2, \ldots, v_n\}$ and the edge set $E(t) = \{\varepsilon_1(t), \varepsilon_2(t), \ldots, \varepsilon_m(t)\}$. The adjacency matrix is $A(t) = [a_{ij}]$. When the value of each element a_{ij} in the adjacency matrix is neither 0 nor 1, the graph $G(t)$ is called a weighted graph.

Assuming that $x_i \in R_m$ ($i \in V$, $m = 2$ or 3) represents the location information of the agent i, it should contain three dimensions in actual situations. According to matrix theory, the position matrix $[x] = \mathrm{col}(x_1, x_2, \ldots, x_n)$ is the position matrix of each agent in the figure. Through the position information, the matching of speed information and acceleration information can be completed.

The multi-agent-aware network model is:

$$\begin{cases} \dot{x}_i = v_i \\ \dot{v}_i = a_i \end{cases} \tag{1}$$

Agent perception range: A perceptible range is defined for each agent. This range is a geometric sphere with the agent as the center of the sphere and a radius of r. The geometry of its perception range is expressed as

$$N_i = \{j \in v : \|x_i - x_j\| < r\} \tag{2}$$

3 Optimized Olfati-Saber Algorithm

3.1 Olfati-Saber Second Algorithm

Gradient Expressed with σ Norm. The σ norm is a mapping from R_m to $R \geq 0$, the mathematical definition of the σ norm and its gradient morphology is

$$\|z\|_\sigma = \frac{1}{\varepsilon}\left[\sqrt{1+\varepsilon\|z\|^2} - 1\right] \tag{3}$$

$$\sigma_\xi = \frac{z}{\sqrt{1+\varepsilon\|z\|^2}} = \frac{z}{1+\varepsilon\|z\|_\sigma} \tag{4}$$

where ε is a non-negative parameter that can be set.

Collision Function and Adjacency Matrix. The collision function is a typical scalar function with a domain between [0, 1] and a smooth function. The mathematical expression of the collision function is as follow

$$\rho h(z) = \begin{cases} 1, z \in [0, h) \\ \frac{1}{2}[1 + \cos(\pi \frac{z-h}{1-h})], z \in [h, 1) \\ 0, \text{others} \end{cases} \tag{5}$$

It can be seen from the expression that when $h = 1$, the collision function is a constant function, that is, the value in the interval [0,1] is 1, and the function value in the other intervals is 0.

On this basis, each element in the spatial adjacency matrix $A(x) = [a_{\mathrm{ij}}]$ is defined as

$$a_{ij}(x) = \rho h(\frac{\|x_j - x_i\|}{r_\alpha}) \in [0, 1], j \neq i \tag{6}$$

Potential Energy Function. In order to describe a complete and smooth potential energy function, a force equation $\Phi_\alpha(z)$ is integrated here. According to the definition of the perception range of the agent, the function value of $\Phi_\alpha(z)$ is 0 when the perception range exceeds $z \geq r_\alpha$. In the perception range of the agent, the mathematical expression of the force equation is

$$\varphi_\alpha(z) = \rho h(\frac{z}{r_\alpha})\varphi(z - d_\alpha) \tag{7}$$

$$\varphi(z) = \frac{1}{2}[(a+b)\sigma_1(z+c) + (z-b)] \tag{8}$$

And due to $0 < a < b$, $c = |a-b|/\sqrt{4ab}$, $\Phi(0) = 0$.

It is precisely because of the possible existence of "squadrons" that Saber's second algorithm was born. The algorithm pre-sets a virtual leader with a fixed speed. All other agents in the group need to follow this virtual leader and the team needs to advance together with a geometric structure similar to α lattice. In the mathematical model, the algorithm has been simply improved on the basis of Saber's first algorithm. In addition to the gradient and speed feedback items, the acceleration input also adds navigation feedback items to reflect the role of the fixed speed virtual leader. The new acceleration input is expressed as follows

$$a_i^\alpha = \sum_{j \in N_i} \varphi_\alpha(\|x_j - x_i\|_\sigma)n_{ij} + \sum_{j \in N_i} a_{ij}(x)(v_j - v_i) + f_i^r(x_i, v_i, x_r, v_r) \tag{9}$$

Among them, f_i^r (x_i, v_i, x_r, v_r) is a newly added navigation feedback item, and its mathematical expansion is

$$f_i^r(x_i, v_i, x_r, v_r) = -c_1(x_i - x_r) - c_2(v_i - v_r), c_1 > 0, c_2 > 0 \tag{10}$$

Among them, c_1, c_2 are two non-negative constants. x_r represents the position information of the virtual leader, and v_r represents the speed information of the virtual leader.

3.2 Olfati-Saber Model with Variable Speed Virtual Leader

In order to stabilize and converge the optimized shift leader model, a more complete set of theories must be used to prove and further optimize. In this paper, each agent (including the virtual leader) in the group is subjected to the same form of acceleration input, which can not only ensure the stability of the entire model, but also make the entire movement process convergence speed become faster.

The principle is to input acceleration to the virtual leader in the same form on the basis of the second algorithm of Olfati-Saber. Since the virtual leader itself does not need to be led by itself, the acceleration input of the virtual leader becomes

$$a_i^\alpha = \sum_{j \in N_i} \varphi_\alpha(\|x_j - x_i\|_\sigma)n_{ij} + \sum_{j \in N_i} a_{ij}(x)(x_j - x_i) \tag{11}$$

4 Simulation Results

The number of drones set by simulation is 50, of which the parameter settings are $\varepsilon = 0.1, h = 0.9, c_1 = 0.1, c_2 = 0.2$. The simulation time interval is set to 0.1 s, a total of 1000 cycles. By randomly generating the position and initial speed of the drone, each agent is clustered after each iteration through successive calculations. The blue circle in the figure represents the agent, and the red arrow represents the current direction of the agent. Since the position information and speed information of each simulation are randomly generated, only the results of a certain simulation are shown here.

4.1 Olfati-Saber Second Algorithm

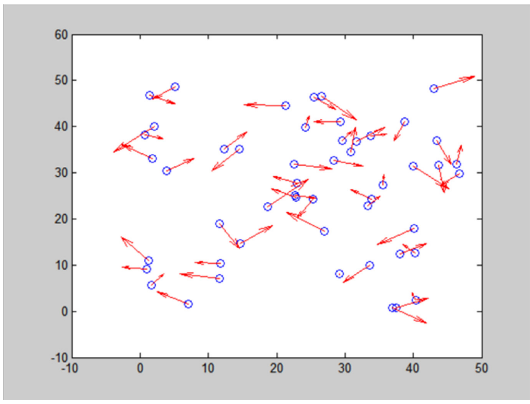

Fig. 1. UAV space arrangement based on Olfati-Saber second algorithm (t = 0)

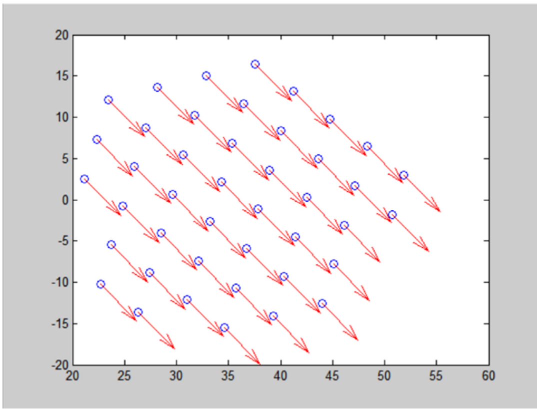

Fig. 2. UAV space arrangement based on Olfati-Saber second algorithm (t = 1000)

The speed direction is expressed by the unit vector of speed information, so the range of values in the figure is [−1, 1]. Figure 3 shows the x-direction agent's speed following situation, and Fig. 4 shows the y-direction agent's speed following situation. The red horizontal line in the figure represents the speed of the virtual leader at a fixed speed, and the other blue curves represent the speed changes of the remaining 49 agents (Figs. 1 and 2).

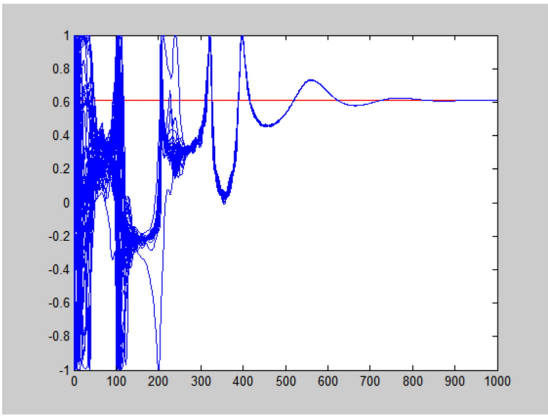

Fig. 3. X-direction agent speed following based on Olfati-Saber second algorithm

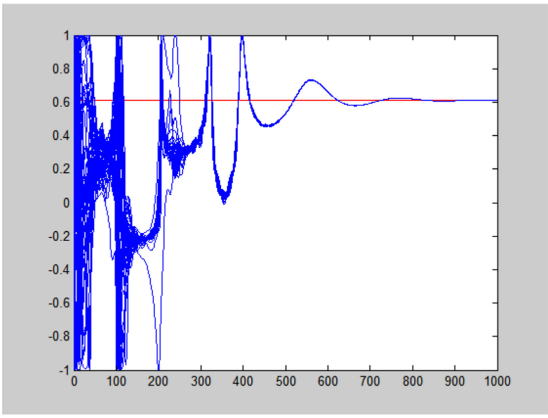

Fig. 4. Y-direction agent speed following based on Olfati-Saber second algorithm

4.2 Olfati-Saber Model Based on Variable Speed Virtual Leader

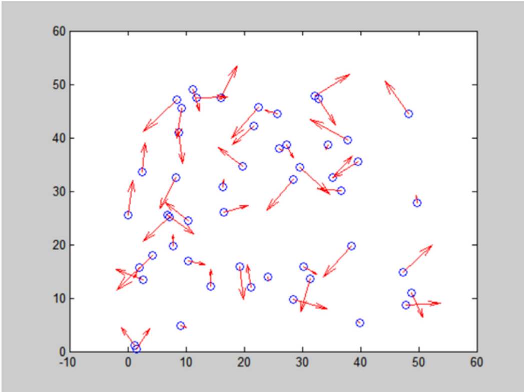

Fig. 5. UAV space arrangement based on model with variable speed virtual leader (t = 0)

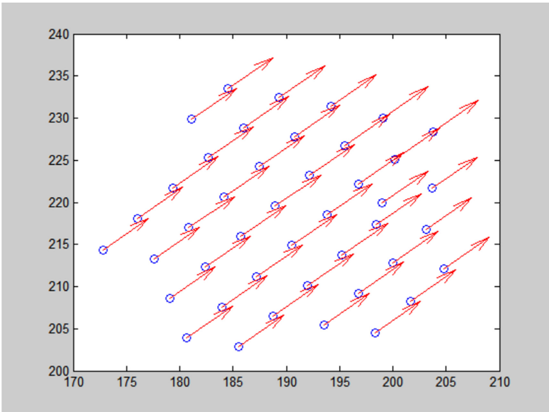

Fig. 6. UAV space arrangement based on model with variable speed virtual leader (t = 1000)

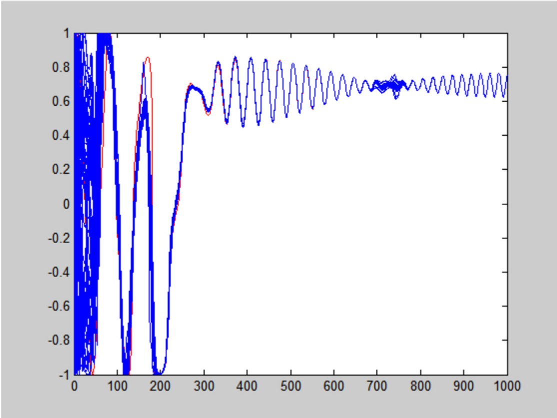

Fig. 7. X-direction agent speed following based on model with variable speed virtual leader

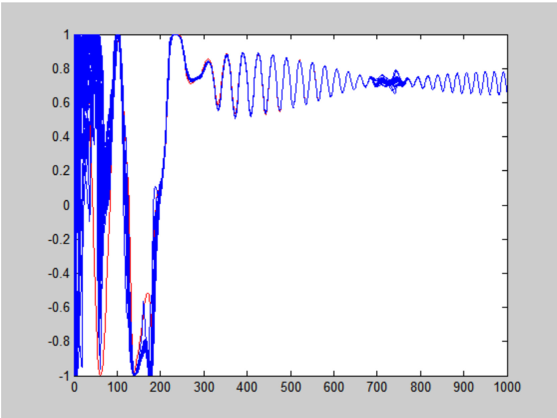

Fig. 8. Y-direction agent speed following based on model with variable speed virtual leader

Through simulation, we can find that the efficiency of the variable speed virtual leader algorithm is much higher than that of the fixed speed virtual leader, and the calculation convergence is fast. It can be seen from the situation that the speed of the agent follows, although the speed of the virtual leader is constantly changing, other agents can still quickly change the direction of the speed (Figs. 5, 6, 7 and 8).

5 Conclusion

In this paper, we proposed an optimized Olfati-Saber algorithm in order to make the group speed converge faster. With the variable speed virtual leader, the new system model is more efficient than before, which proves that the Olfati-Saber algorithm of the variable speed virtual leader has good feasibility and effectiveness, and expands the application prospect of complex UAV systems.

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