Aerospace Systems
https://doi.org/10.1007/s42401-023-00238-1

ORIGINAL PAPER

Intention recognition of UAV swarm with data-driven methods

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Received: 7 February 2023 / Revised: 9 May 2023 / Accepted: 15 June 2023

Abstract

UAVs have been increasingly used in military and commercial applications. The theory of UAV swarm behavir has gradually matured and moved to the real application stage. Fast and accurate recognition of the intentions of UAV swarms become a key part of dealing with coming swarms. This paper proposes a data-driven approach to realize the recognition of the typical intentions of UAV swarm. The UAV swarm's intention is divided into three basic categories: expansion, free movement, and contraction. The dubins model is introduced to depict and study the dynamic characteristics of the movement of the UAV swarm. Simulation experiments are performed through software to collect data and to verify and refine the proposed data-driven intention recognition approach. Moreover, real flight experiments are conducted to test the feasibility and accuracy of the proposed approach, from which key steps about the neural network building and training for intention recognition have been summarized, and satisfying results in intention recognition with high accuracy and stability during the entire movement of the UAV swarm have been achieved.

Keywords Swarm · Data-driven · Dubins model · Intention recognition

1 Introduction

An Unmanned Aerial Vehicle (UAV) is an aerial platform that is autonomous/semi-autonomous or remotely controlled to accomplish its mission. A swarm is a large number of animate or inanimate agents massed together and usually in motion or a formation with specific intentions. A UAV swarm refers to a coordinated group of multiple UAVs that are operated and controlled together to achieve a common goal. These UAVs are typically equipped with sensors, communication devices, and control algorithms that allow them to fly in a synchronized manner, and to perform complex tasks such as search and rescue, surveillance, and reconnaissance missions efficiently.

The intentions of UAV swarms are associated with their mission objectives. Particularly, in the context of the increasingly intricate aerial combat scenario, the ability to accurately recognize the intentions of the opposing UAV swarm is crucial for the efficient tactical response, target assignment, and maneuver determination. Therefore, intention recognition of UAV swarm has attracted a great deal of interest [1, 2]. Currently, there are two prominent methodologies for recognizing the intentions of UAV swarms, namely the model-based approach and the data-driven approach.

The model-based approach to intent recognition for UAV swarms encompasses techniques such as finite parametric models and Bayesian network methods. This approach primarily concentrates on defining the functional form of nonlinearities, as well as the tactical application and interdependence of variables associated with air targets. As stated in [3], the critical challenge in the application of methods based on the estimation of models within a finite parametric class is the proper selection of the model class. This is typically achieved through a search process that progresses from simple models, such as linear, bilinear, polynomial, and neural networks, to more complex ones. Specifically, a Bayesian network approach for recognizing air-target combat

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Published online: 05 July 2023

attempts is proposed in [4]. The method involves analyzing various parameters, such as speed and distance, to construct a Bayesian network that can identify the operational intention of the air target. The parameters of the network are determined through an analysis of past tactical applications of the target, reflecting the dependence between variables. However, the approach's lack of a standardized structure leads to a certain degree of subjectivity in the construction process, which in turn limits the accuracy of the evaluation results. In [5], a Multi-Entities Bayesian Network (MEBN) approach for recognizing air target intentions in tactical scenarios is proposed. The MEBN methodology utilizes local knowledge in the form of MEBN fragments, consisting of local random variables and their interrelationships, which are reorganized under specific constraints. The tactical intention of an enemy air target is identified based on the posterior probability distribution of the target variables. However, there is a subjective element in determining the consistency constraints between MEBN fragments, and varying constraint determinations can result in significant variations in recognition results. This challenge arises due to the difficulty in obtaining meaningful descriptions of model uncertainty in nonlinear parametric models, whose parameters are often obtained through physical modeling or data-driven identification methods, making it complicated to estimate [6].

In contrast to the model-based approach, a data-driven method does not depend on the significance or interrelationship of the variables. Instead, a learning network is created as a black box to execute the task of intention recognition, without requiring a comprehension or justification of the system [7]. In [8–10], a Long and Short-Term Memory (LSTM) model is introduced to predict air combat target intent, specifically for addressing the challenge of UAV air combat target intent prediction under non-complete information. In [11], a Markov Chain Monte Carlo (MCMC) random sampling algorithm that uses the topological sequence as its search space is proposed, where a two-step approach focusing on the transfer network's unique temporal expansion structure is incorporated in a self-adaptive mechanism of the genetic learning algorithm to identify the intention. In [12], a mathematical model for airborne target intent recognition is developed, utilizing Fisher and Bayes discriminant as the classifier to formulate target intent recognition principles. In [13], an air target attack intent determination model based on Intuitionistic Fuzzy Generative Rule inference (IFGR) and multi-attribute decision-making is designed. Nevertheless, due to that the dynamic characteristics of UAV swarm movement are ignored and comprehensive analysis for selecting parameters/data that described the swarm intention is lacking, the outcomes of the above-mentioned approaches are overly optimistic or oversimplified, rendering them of limited practical value. Recently, a supervised learning model is proposed in [14] for predicting the formation of UAV swarm targets. The model employs the softmax regression as the machine learning classifier and the Robot Operating System (ROS) as the simulation platform. However, the study only considered simple geometric formations and assumed homogeneous linear motion for all transformations, which may be unrealistic for real-world applications.

This study utilizes a data-driven learning approach with the incorporation of the UAV swarm motion model for intention recognition. The data is generated under the guidance of the motion model to increase the realism of the UAV swarm's motion through the addition of constraints and diversity. Additionally, the data is filtered to evaluate the effects of the obtained parameters on the prediction results, in order to scrutinize and optimize the training of the neural network. Particularly, several similar networks with different types of input data were built to compare and select useful and valuable parameters of the swarm movement. To verify the feasibility of the proposed UAV swarm intention recognition method, simulations and experiments are conducted on a swarm made up of three quadrotors.

2 Problem statement and methodology

2.1 UAV swarm modeling

To gain insight into the intention of UAV swarms and to gather scientific data for data-driven methodologies, a preliminary examination of the UAV swarm model was conducted.

Dubins model [15–17] is a simplification of the motion of a single UAV agent. It simplifies the movement into a one-way, forward-facing motion pattern. Several UAV agents with such a motion pattern can cooperate and form a swarm. Every agent follows its movement pattern within the swarm while also interacting with other agents. The motion of each swarm agent can be described by the following equation [15]:

$$p_{x,k+1} = p_{x,k} + u_{\mathrm{s}} \cos(\theta_k)\, \delta_t + \omega_{px,k} \tag{1}$$

$$p_{y,k+1} = p_{y,k} + u_{\mathrm{s}} \sin(\theta_k)\, \delta_t + \omega_{py,k} \tag{2}$$

$$\theta_{k+1} = \theta_k + \frac{u_{\mathrm{s}}}{L} \tan\left(u_\phi\right) \delta_t + \omega_{\theta,k}, \tag{3}$$

where the p_x and p_y are the x and y coordinates of the agent and θ is the yaw angle of the agent, L is the length of the UAV agent from the head to the rear tires, u_{s} is the speed of the agent, δt is the sampling time, $\omega_{px,k}$, $\omega_{py,k}$ and $\omega_{\theta,k}$ represent random noises, respectively. A reference signal $\theta_{\mathrm{desired}}$ based on the real-time centroid of the swarm (c_x, c_y) is given as follows:

$$\theta_{\mathrm{desired}} = \arctan 2\left(c_y - p_y, c_x - p_x\right) \tag{4}$$

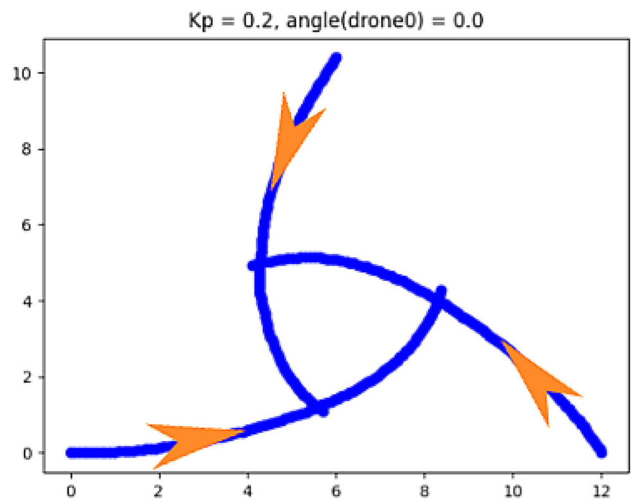


Fig. 1 The path of the UAV swarm under the intention of contraction

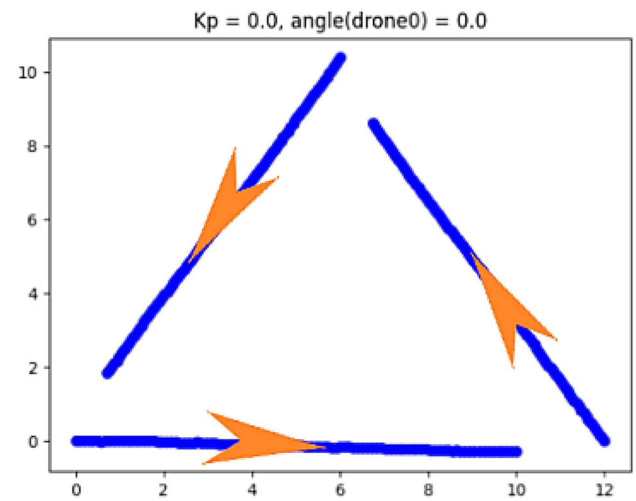


Fig. 2 The path of the UAV swarm under the intention of free movement

The agents use this reference signal to design a feedback controller according to the proportional control law as follows:

$$u_{\phi} = \min\left\{\theta_{\max}, \max\left[\theta_{\min}, K_{\mathrm{p}}\left(\theta_{\mathrm{desired}} - \theta\right)\right]\right\}, \tag{5}$$

where the steering angle of each agent is guaranteed to be within $[\theta_{\min}, \theta_{\max}]$ rad. The parameter denoted as K_{p} in this research serves as a crucial factor that influences the movement behavior of the UAV agent. Specifically, a positive value of K_{p} results in an inward movement of the UAV agent towards the centroid, aimed at approaching the centroid. Conversely, a negative value of K_{p} induces an outward movement of the UAV agent away from the centroid, aimed at moving away from the centroid. When K_{p} is set to zero, the UAV agent exhibits autonomous movement behavior, disregarding the centroid. This definition of K_{p} in the context of the study elucidates its significance as a determinant of the motion properties of the UAV agent in the experimental setting and underscores its role in shaping the intentional behavior of the UAV swarm.

To deal with a swarm made up of three UAV agents, exactly the study object of this paper, motion data of the swarm can be obtained by iterating until the set end.

Although the intentions of the UAV swarm are very diverse, all these complex intentions can be seen as the permutations and combinations of three elementary intentions: contraction, free movement, and expansion. The definitions of these three intentions are given as follows:

Definition 1 (*Contraction*) An intention of contraction is presented when the swarm intends to move towards the centroid of the swarm.

Definition 2 (*Free movement*) An intention of free movement is presented when the UAV agents intend to move straightforwardly on their own.

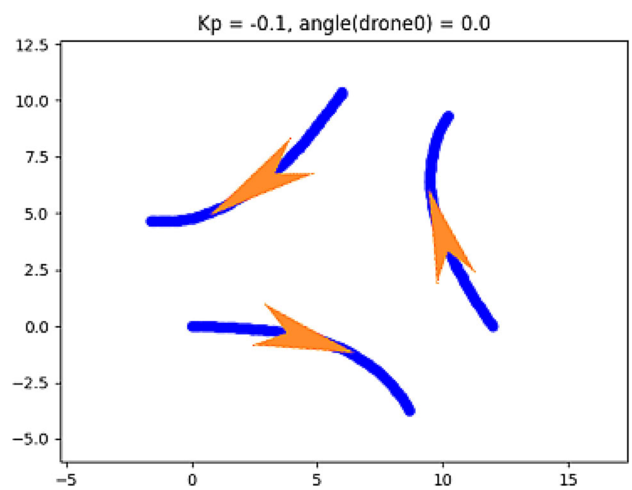


Fig. 3 The path of the UAV swarm under the intention of expansion

Definition 3 (*Expansion*) An intention of expansion is presented when the swarm moves away from the centroid.

According to the UAV dynamic model in Eqs. (1)–(3) and the controller in Eq. (5), it is clear that different intentions of the UAV swarm can be governed by choosing different values of the control gain K_{p}. If $K_{\mathrm{p}} > 0$ in Eq. (5), the swarm is under the intention of contraction, which is demonstrated in Fig. 1 with a gathering flying path generated by setting $K_{\mathrm{p}} = 0.2$. If $K_{\mathrm{p}} = 0$ in Eq. (5), the swarm is under the intention of free movement, which is demonstrated in Fig. 2 with a free-moving flying path generated by setting $K_{\mathrm{p}} = 0$. Similarly, if $K_{\mathrm{p}} < 0$ in Eq. (5), the swarm is under the intention of expansion, which is demonstrated in Fig. 3 with a expanding flying path generated by setting $K_{\mathrm{p}} = -0.1$.

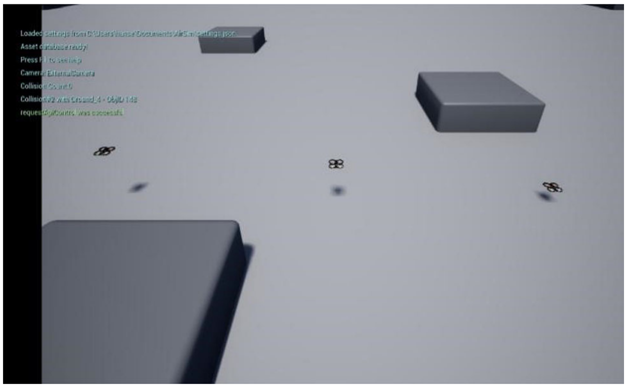


Fig. 4 Airsim simulation platform

2.2 Problem statement

The problem of interest to this paper is listed below.

Problem 1 *For a given UAV swarm made up of three agents with their initial positions being an equilateral triangle and the movement pattern of the swarm described by the dubins model in Eqs.* (1)–(3)*, let the movement start at* $T = 0$ *and end at* $T = t$*, then an algorithm is to be designed to recognize the intention of the swarm correctly (identify the intention from one of the three basic intentions defined in Definitions* 1*,* 2 *and* 3*) before* $T = t/2$.

2.3 Methodology

In this section, tools and methods employed for the determination of the intention of UAV swarm systems are presented.

2.3.1 Simulation platform

Airsim simulation platform is an extension developed by Microsoft based on Unreal Engine 4 as the underlying framework, specifically for the simulation of vehicles and UAVs. A data exchange API in Python code is widely used in machine learning and other fields since a large amount of reliable data can be obtained without losing the accuracy of motion, which can be used as training and test data for neural networks. Figure 4 shows a screenshot during one simulation experiment in the Airsim platform with three quadrotors hovering.

The Airsim platform interaction repository, including control, collision avoidance, data transmission and shutdown, etc., has been integrated into the self-made "Information-Recognition" (IR) library. It is particularly noted here that the collision avoidance program in the IR library is an algorithm designed independently after the simulation found that the simulated UAVs may collide and entangle with each other. In the stage of simulation, we set $L = 98$ mm, $u_s = 20$ cm/s, $\delta t = 0.8$ s in the UAV model given in Eqs. (1)–(3) and $\theta_{\max} = \frac{\pi}{8}$, $\theta_{\min} = -\frac{\pi}{8}$ with different control gains K_p in the controller given in Eq. (5) to generate the coordinate and velocity data of the swarm under different intentions. Then, during the simulation, by entering the coordinate and velocity data generated by the UAV model and controller into the program, the simulated UAV in the Airsim platform can be controlled to fly exactly according to the calculated path. Then a set of real-time recordings of various coordinate parameters and motion parameters during the flight, plus some calculations and processing, is obtained and saved. The dataset's detail and selection will be further introduced and analyzed in Sect. 3.1.

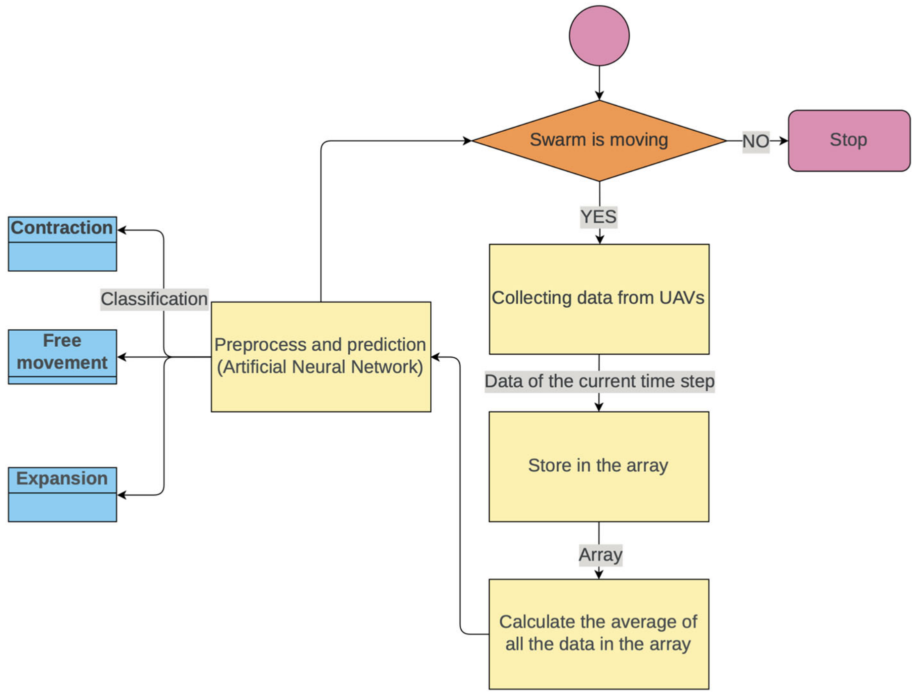
2.3.2 UAV experiment platform

The DJI Tello UAV has been utilized in actual flight experiments, incorporating a built-in application programming interface (API) data port that enables real-time transmission of computer-generated commands to the UAV through a local area network (LAN). Additionally, the motion parameters obtained by the sensors on the UAV can be concurrently relayed back to the computer, thus facilitating simultaneous command transmission and data retrieval through the same device.

Initialization of DJI Tello UAV (hereinafter also referred to as UAV), including UAV-fixed frame orientation calibration, multi-UAV networking, control program testing, etc., is the first step of the real flight experiment. In the control program, the paths obtained from the UAV model, which are smooth curves, are superimposed by multiple minor linear displacements. However, since the UAVs execute the codes completely line by line, i.e., the command will be executed only if the previous one is completely completed, the characteristics of this program execution are manifested in the discontinuity of the UAV movement. To solve this problem, we use high-quality LAN to increase the frequency of sending commands to eliminate the pause in the motion of UAVs and improve the smoothness of the UAV movement.

In the real flight experimental site, the initial position of the three UAVs is an equilateral triangle with a side length of 4 ms, the initial orientation is along the edge of the equilateral triangle, and the path coordinate points are marked with tape and markers, as shown in Fig. 5. Also, other parameters like the fuselage length L and flight speed u_s were changed according to the real condition of UAVs. Through the control program of the UAV, while sending the motion command to the UAV, the command requiring the UAV to return the data is sent simultaneously, and the UAV will return the data collected by the sensor instantly. After completing a flight, we process the saved flight data and substitute it into the neural network to output the results.

Fig. 6 The flow chart of the algorithm of intention recognition



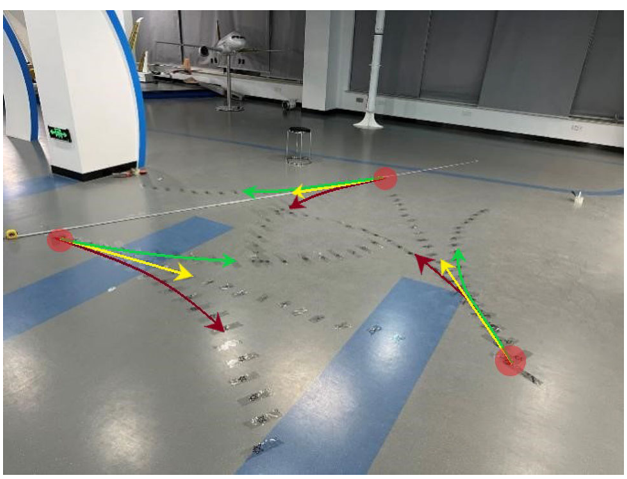


Fig. 5 Experimental site (the tape and marker marks are the coordinate points on the paths, the tape measure is placed on the x-axis, the red dot marks are the starting points of the three UAVs, and the arrows in red, yellow and green indicate the paths under the intentions of contraction, free movement and expansion, respectively)

2.3.3 Algorithm

The logic of the algorithm used for intention recognition is shown as the flow chart in Fig. 6.

The system will first determine whether the UAV swarm is in motion. If not, the program terminates or goes into hibernation. If yes, the system will gather the data of interest, which is the optimal selection of data that will be further introduced in Sect. 3.1.

The current state of the swarm's motion is recorded and stored in an array, which serves as a historical database. Subsequently, the average of the stored data is calculated to gain insight into the general behavior of the swarm over time. The reason why the average of current and historical data is used rather than only current data is that both the motion and the intention of the swarm are continual, and current data can include environmental and internal deviations.

After the normalization of the average data, the input of the artificial neural network is obtained. Here a MultiLayer Perceptrons (MLP) is designed with the help of Keras, which is an advanced neural network API written in Python that can run on TensorFlow. The structure of the neural network is shown in Fig. 7. The neural network consists of one dense input layer and three dense layers (including one dense output layer). The activation of these layers are relu, and softmax is specially used in the output layer which is not marked in the figure.

MLP is suitable for classification prediction problems where inputs are assigned a class or label. Compared with other popular types of artificial neural networks such as the Convolutional Neural Network (CNN) and the Recurrent Neural Network (RNN), MLP has the best performance in classification [18].

The output of the neural network will be a one-hot encoding. The label for expansion intent is [0, 0, 1], the label for free movement intent is [0, 1, 0], and the label for contraction intent is [1, 0, 0]. The program will pick the largest one from the three-dimensional output and set it as the final classification. Finally, the outcome will be compared with the K_{p}

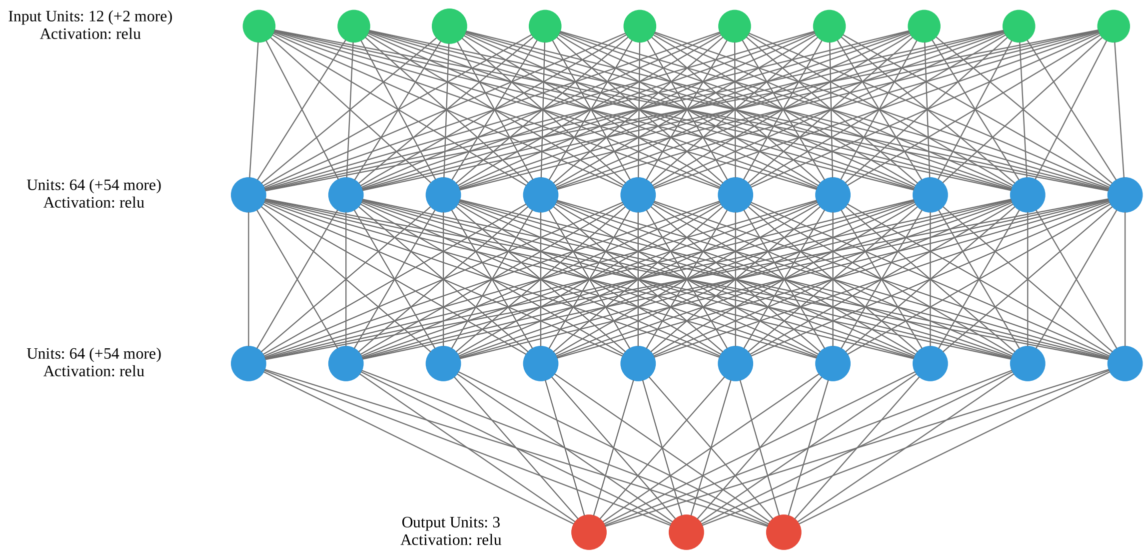


Fig. 7 The structure of the artificial neural network used to predict the intention of the UAV swarm

value set in the UAV model to verify the classification of the neural network.

3 Main results

3.1 Data selection

Data collected from the UAV agents includes the line velocity v (3-dimensional), angular velocity ω (3-dimensional), line acceleration a (3-dimensional), angular acceleration α (3-dimensional), orientation n (4-dimensional), rotation angle under the real-time centroid polar coordinates system of the UAV swarm θ (one-dimensional and hereinafter referred to as the rotation angle) and distance from the real-time centroid of the UAV swarm r (1-dimensional) of every agent respectively, and spacing d (in x, y and z direction). All these parameters make up the piece of data of one step. In all, there are 63 columns in one piece of data.

Since there is a large number of parameters in the data, a very heavy neural network and a highly complex data collection system are required to process and catch all the data, respectively. Therefore, one missing parameter can lead to a disaster in this case. To reduce the complexity of the neural network and improve its reliability, a test on different combinations of the parameters is conducted.

First, one type of parameter is set as the input at a time, while the structure and the times of training of the neural network keep the same and the remaining parameters are set to zero. The results of loss value and accuracy are shown in Figs. 8 and 9. It can be concluded that the loss values of different types of parameters are quite distinct, while the accuracy distribution is more concentrated. It observed from Figs. 8 and 9 that the four parameters with the lowest loss values are angular acceleration α, angular velocity ω, spacing d, and linear acceleration a; and the parameters with the highest accuracy are linear acceleration a, angular acceleration α, angular velocity ω, and rotation angle θ.

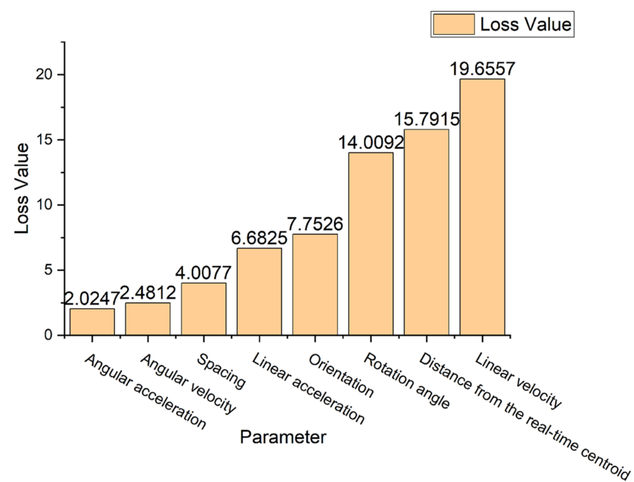


Fig. 8 Loss value of single parameter input

In view of these results, a further study is carried out on the combinations of angular acceleration, angular velocity, distance, linear acceleration, and rotation angle. The following Group Set I containing a total of 6 research groups is set up as follows:

1. Group 01: angular velocity + linear acceleration + angular acceleration + spacing + rotation angle;
2. Group 02: angular velocity + linear acceleration + angular acceleration + spacing;

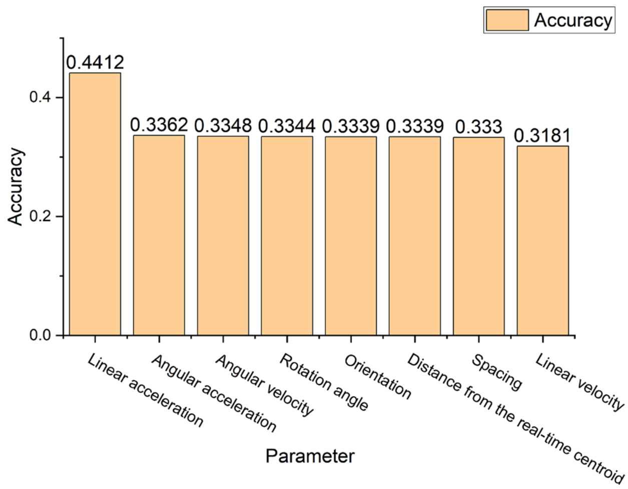


Fig. 9 Accuracy of single parameter input

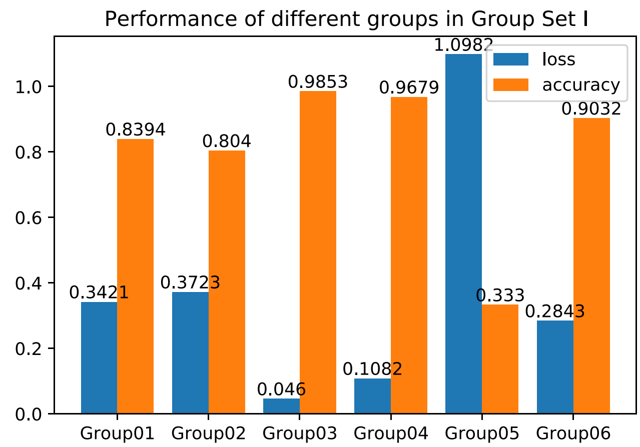


Fig. 10 Performance of different groups in Group Set I

3. Group 03: angular velocity + linear acceleration + angular acceleration + rotation angle;
4. Group 04: angular velocity + linear acceleration + spacing + rotation angle;
5. Group 05: angular velocity + angular acceleration + spacing + rotation angle;
6. Group 06: linear acceleration + angular acceleration + spacing + rotation angle.

The first group in Group Set I contains all the parameters, which are used as a standard for comparison. One type of parameter is removed from the remaining groups respectively. The results are shown in Fig. 10. In the evaluation of the performance of a specific group, the final loss and accuracy metrics are employed. The loss value serves as an objective function that is minimized during the training process of the neural network. It quantifies the dissimilarity between the predicted output and the actual output (ground truth) for a given dataset. Lower loss values indicate a higher degree of agreement between the predicted and actual outputs, while higher loss values imply a poorer alignment. On the other hand, the accuracy value is a measure of the performance of the intention recognition algorithm, indicating the percentage of correctly predicted intentions out of the total number of intentions. It is a widely used metric for evaluating the accuracy of a classification algorithm, where higher accuracy values denote superior performance in correctly predicting the intentions of the UAV swarm. Group 05, without the parameter linear acceleration, gains the poorest accuracy and the highest loss. It can be determined that linear acceleration is a key parameter, and will be reserved in the follow-up study. Similarly, the results of Group 02 are the second worst, so its default parameter rotation angle can be reserved; Group 03 and Group 04 have the best outcomes in the experiment, based on which the follow-up study can be carried out:

Based on the results above, the combination of three types of parameters is then studied, and the following Group Set II including 5 subgroups is set:

1. Group 03-1: linear acceleration + angular acceleration + rotation angle;
2. Group 03-2: angular velocity + linear acceleration + rotation angle;
3. Group 03-3: angular velocity + linear acceleration + angular acceleration;
4. Group 04-1: linear acceleration + spacing + rotation angle;
5. Group 04-2: angular velocity + linear acceleration + spacing.

As shown in Fig. 11, except that the results of Group 04-2 in Group Set II are slightly worse, the accuracy and loss values of the five groups are acceptable. Group 03-2 and Group 04-1 with the best results have the same missing parameter: angular acceleration; and Group 04-2 with the poorest results has the missing parameter: rotation angle.

Based on all the previous results, it can be inferred that linear acceleration and rotation angle are the two most critical types of parameters. Therefore, a model combined with linear acceleration and the rotation angle is built, and the result is that the loss value is 0.0687 and the accuracy is 0.9747, which are a bit worse but very close to the previous Group 03-2 and Group 04-1.

It can be also concluded that the existence of linear acceleration and rotation angle greatly affects the neural network's performance. Adding other parameters properly can further optimize the model such as the angular velocity, but adding too many parameters may lead to the deterioration of the results.

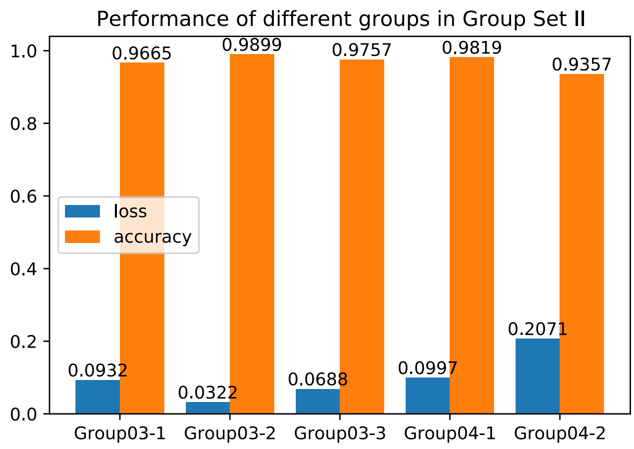


Fig. 11 Performance of different groups in Group Set II

Table 1 Multi-class neural network structure

Layer (type)	Output shape	Param #
dense(Dense)	(None, 64)	3520
dense_1(Dense)	(None, 3)	195

Table 2 Two-class neural network structure

Layer (type)	Output shape	Param #
dense(Dense)	(None, 64)	3520
dense_1(Dense)	(None, 64)	4160
dense_2(Dense)	(None, 1)	65

3.2 Neural network

To make the neural network perform better, the structure and optimizer of the network are studied in this subsection.

Two different concepts for the neural network architecture have been proposed, with one suggesting the construction of a multi-class neural network and the other advocating for the development of three separate two-class neural networks, each responsible for binary classification of a specific intention. The multi-class neural network exhibits a simpler architecture and provides higher accuracy for balanced datasets. However, it has limited interpretability and is challenged when dealing with imbalanced datasets. On the other hand, the two-class neural network offers good interpretability and robustness to imbalanced datasets. However, it is less efficient when tackling multi-class classification tasks and shows reduced accuracy for balanced datasets. The selection of the neural network model is contingent on the specific classification task and dataset characteristics. If the dataset is balanced, the multi-class neural network may prove to be the more advantageous choice, whereas a two-class neural network may be more suitable when working with imbalanced datasets. Furthermore, the requirement for interpretability may also influence the selection of a neural network architecture.

Table 1 depicts the architecture of a multi-class neural network, comprising two dense (fully connected) layers. This neural network is specifically designed for classification tasks that involve three output classes. In contrast, Table 2 illustrates the structure of a two-class neural network, which consists of three dense layers. This particular neural network is tailored for binary classification tasks with two output classes. By utilizing three instances of such two-class neural networks, each assigned to the binary classification of a specific intention, it becomes possible to achieve the classification of three different types of intentions.

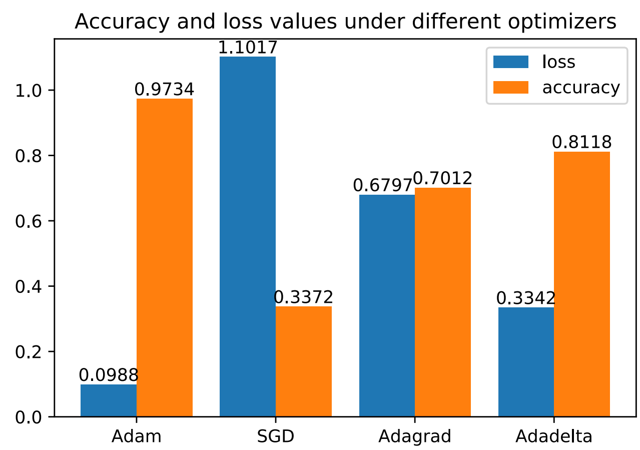


Fig. 12 Comparison of the different optimizers

Upon conducting training with an identical dataset and duration, the multi-class neural network achieves an accuracy of 80%. In contrast, the three two-class neural networks demonstrate varying accuracy levels of 89.9%, 75.4%, and 89.9%, respectively. These findings suggest that the performance of the two-class neural networks in binary intention classification is not consistent and may lead to contradictions or invalidations. Also, the dataset used in this research is generated by the simulation experiment which is quite completed and balanced. Consequently, the utilization of a multi-class neural network may be preferred in order to ensure overall stability in subsequent experiments.

For the selection of the optimizer, a comparative experiment of the optimizers based on the same training dataset, neural network, and training times, is conducted. As shown in Fig. 12, the optimizer "Adam" achieves the highest accuracy and the lowest loss value, while the results using optimizer "SDG" are relatively poor. Therefore, the optimizer "Adam" is used in the subsequent neural network construction.

3.3 Intention recognition

3.3.1 Simulation

The set of parameters selected is that of Group 04-1 in Group Set II and the neural network is also trained based on that. With the algorithm introduced in Sect. 2.3.3, the following results are obtained:

In Fig. 13, the titles indicate the actual duration and intention of the entire movement of the UAV swarm. The horizontal axis represents the time in seconds for intent identification, and the vertical axis represents the probability of intent recognition. The green, yellow, and red spots represent the intents of expansion, free movement, and contraction, respectively. The diagrams suggest that the previously designed neural network can provide stable and accurate intention judgments in the first half of the movement.

However, it is observed that the output of the neural network is unstable at the beginning of the movement. This instability is attributed to the fact that the training data for the neural network is based on the average value of the first half of the entire movement data, which is a relatively longer duration compared to the initial stage. Consequently, the neural network fails to detect or learn the characteristics of the data at the very beginning of the movement, resulting in instability in its output. To address this issue, the training data was improved by using a 50-step by 50-step average of all the data, aiming to reduce the instability in the neural network's output.

3.3.2 Real flight experiment

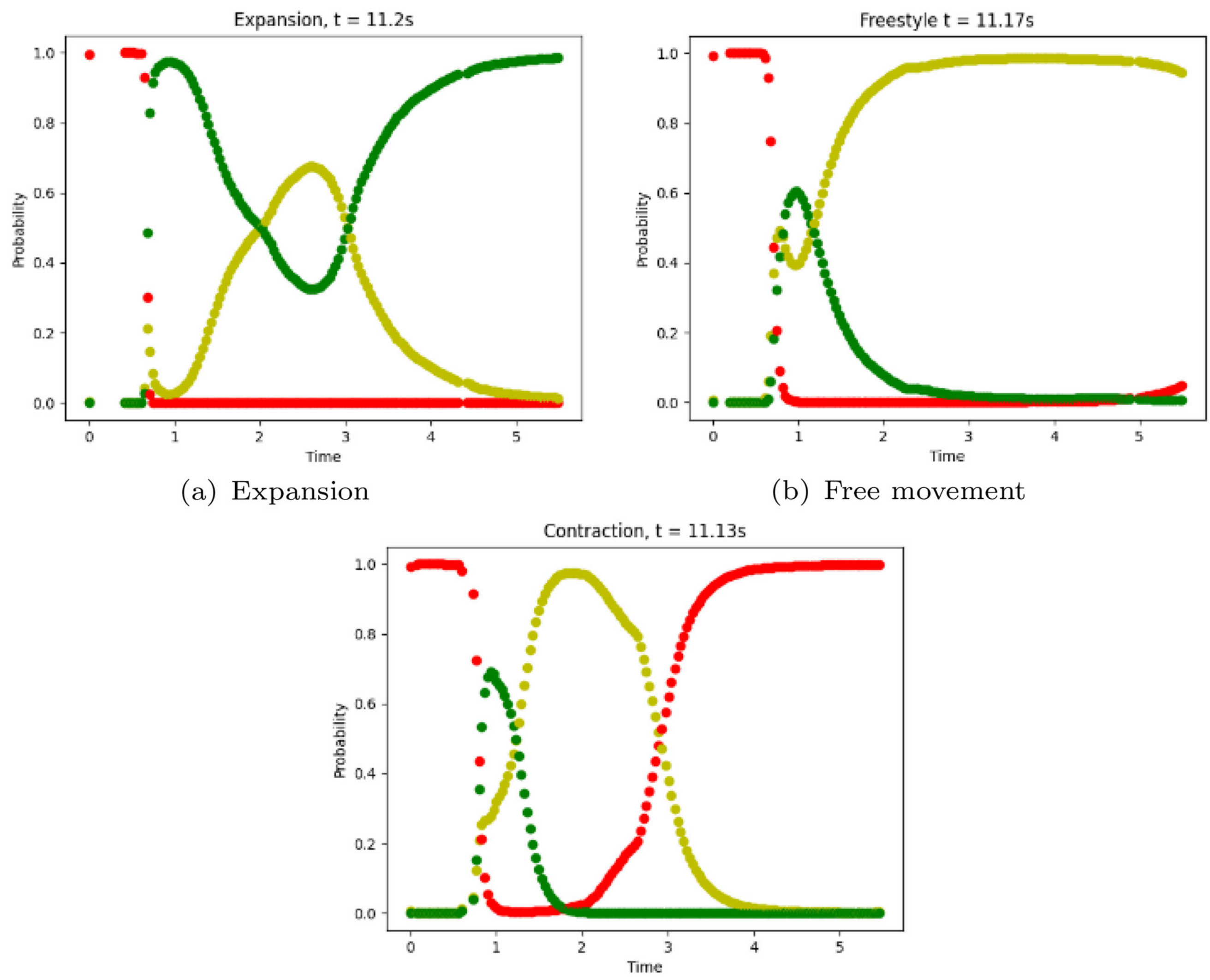
In the flight experiment, the drones are manually controlled to fly along the preset marks on the ground, while the motion parameters are recorded. These recorded parameters are accumulated and averaged step by step before being input into the neural network based on the algorithm. The resulting data, consisting of the number of steps and the corresponding neural network prediction results, are plotted on three scatter diagrams as depicted in Fig. 14. In this experiment, the K_{p} value is used to represent the behavioral intention, as there is a one-to-one correspondence between the K_{p} value and the intended behavior. Specifically, the typical value $K_{\mathrm{p}} = 0$ represents the intention of free movement.

Based on the scatter diagrams presented in Fig. 14, it can be observed that the neural network exhibits a high accuracy in predicting the behavioral intention of the UAV swarm. The results indicate that the neural network is capable of forming accurate judgments throughout the entire movement process of the UAV swarm. This suggests that the neural network is effective in recognizing the intended behaviors of the UAV swarm based on the recorded motion parameters and accumulated data from the flight experiment. The high accuracy of the neural network in predicting the behavioral intention of the UAV swarm implies its potential for real-world applications in handling incoming UAV swarms.

4 Discussion

In the research process of data-driven intention recognition, there are differences in the basic setting between the simulation experiment and the actual flight experiment, including the number of time steps, the value of K_{p}, the cruising velocity, etc., caused by the limited size of the actual experimental site and the limited conditions of the experimental equipment. However, this does not mean that the simulation experiment does not conform to reality or that the actual flight experiment loses its meaning. The simulation experiments are very realistic at various levels. Since Airsim's underlying framework, UR4 has a very good physical engine, its various motion modes, and parameters are completely close to reality. The most important contribution of the simulation experiment is that it verifies that the idea of data-based intent recognition is completely feasible, and through comparative research, the optimal optimizer and optimal parameter combination based on the current simulation results have been found. The core of the network is equally effective in subsequent real flight experiments.

By analyzing the results, it can be found that the neural network in the final flight experiment has very high accuracy in determining the UAV swarm behavioural intent, which indicates that the expected goal is achieved. However, this result needs to be further investigated. The neural network cannot always make such a high-accuracy judgment during experiments, and there are occasional unstable or wrong results. According to the inspection of the abnormal results, it is found that the problem does not appear in the algorithm, but in the data itself. First, the drone's own flight control system and the airflow in the experimental site are unstable due to the current experiment facilities. For example, when the computer sends the command of moving forward to the drone, the actual movement of the drone is not always straightforward, and occasionally there will be left or right deviation, which makes the data collected by the sensor inconsistent with the expected movement pattern of the drone, resulting in a neural network error. Besides, in essence, the drone reads commands one by one, and the nature of its movement is discontinuous, even though the continuity of drone movement could be approached by increasing the frequency of sending commands and reducing the discontinuity to invisible. The discontinuity in movement leads to the existence of the deceleration process and acceleration process, resulting in the distortion of the data. Moreover, the sensor of the drone also has some unclear problems. After checking the



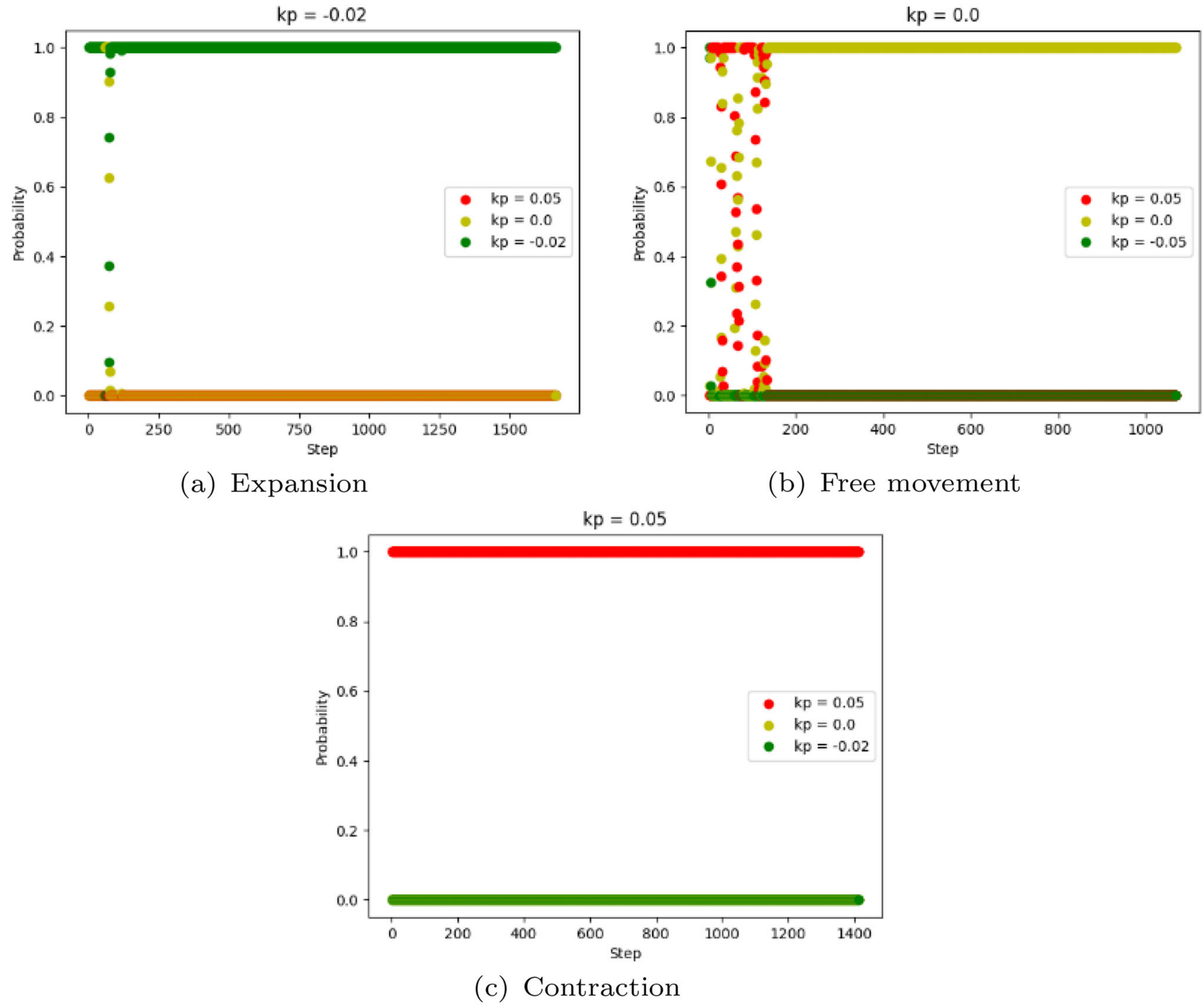
(a) Expansion (b) Free movement (c) Contraction

Fig. 13 The scatter of simulation verification prediction results against the time steps

data, it is found that when the sensor of the drone senses its yaw angle, the self-defined zero-yaw direction (x axis under body-fixed frame) is not fixed, and occasionally there will be a large deviation. At the same time, the direction of the body-fixed frame relative to the ground system also deviates, leading to errors in the data brought into the neural network and abnormal predictions. These deficiencies require further exploration to figure out the causes and solve the problems.

5 Conclusion

In this paper, a data-driven method for recognizing the intention of the UAV swarm is proposed. Instead of looking at UAV flight data in isolation and ignoring the actual UAV swarm dynamics, we combine the dynamic model of UAV swarm movement with neural network construction and training. For the construction of the neural network, different optimizers and parameter selections were tested, and the proper optimizer and parameter combination is found. In terms of data processing, the method of gradually accumulating and averaging is adopted to enhance the neural network's ability to perceive and determine the entire moving process and to improve identification accuracy in the early stage of UAV swarm movement. After analyzing the simulation and experimental test results, it is found that the proposed method can give an accurate and stable identification of the intention during the entire movement process of the UAV swarm. During the entire moving process, the highest accuracy rate can reach more than 98%, and the unstable output accounts for 15% or less of the entire moving process.



(a) Expansion (b) Free movement (c) Contraction

Fig. 14 The scatter of prediction results in real flight experiments against the time steps

Acknowledgements We would like to thank Dr. Xiaohui Zhang, Mr Zeyang Zhao and Mr Xiaoyun Sun from the School of Aeronautics and Astronautics at Shanghai Jiao Tong University for their technical support in our flight experiment.

Funding This work was supported in part by the National Natural Science Foundation of China under Grant No. 62103275.

Declarations

Competing interests The authors have no competing interests.

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