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Model of Collaborative UAV Swarm Toward Coordination and Control Mechanisms Study

Xueping Zhu[1], Zhengchun Liu[2], and Jun Yang[1]

[1] School of Astronautics, Northwestern Polytechnical University, China
zhuxueping@nwpu.edu.cn, yangjun8@nwpu.edu.cn
[2] Computer Architecture & Operating Systems, University Autonoma of Barcelona(UAB), Spain
lzhengchun@caos.uab.es

Abstract

In recent years, thanks to the low cost of deploying, maintaining an Unmanned Aerial Vehicle (UAV) system and the possibility to operating them in areas inaccessible or dangerous for human pilots, UAVs have attracted much research attention both in the military field and civilian application. In order to deal with more sophisticated tasks, such as searching survival points, multiple target monitoring and tracking, the application of UAV swarms is forseen. This requires more complex control, communication and coordination mechanisms. However, these mechanisms are difficult to test and analyze under flight dynamic conditions. These multi-UAV scenarios are by their nature well suited to be modeled and simulated as multi-agent systems. The first step of modeling an multi-agent system is to construct the model of agent, namely accurate model to represent its behavior, constraints and uncertainties of UAVs. In this paper we introduce our approach to model an UAV as an agent in terms of multi-agent system principle. Construction of the model to satisfy the need for a simulation environment that researchers can use to evaluate and analyze swarm control mechanisms. Simulations results of a case study is provided to demonstrate one potential use of this approach.

Keywords: multi-agent system, unmanned aerial vehicles, flight formation, coordination

1 Introduction

Unmanned Aerial Vehicle (UAV) is an aircraft which does not require an onboard pilot. The control of an UAV is usually performed either in an autonomous way by an on-board computer, or in a manual way by an operator remotely in a ground station, or even a mixed semi-autonomous way. Therefore, the pilot safety is no longer a concern. The original and greatest uses of UAV are in military applications. Since the modern technologies make them less expensive and can be made into much smaller sizes to increase their flexibilities. In recent years, unmanned aerial vehicles, have been increasingly utilized by civilian organizations, such as anti-terrorism, disaster management, remote area surveillance and hazardous environment

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monitoring. For instance, after a 6.1 magnitude earthquake struck Ludian County in Yunnan, China, August 2014. Several UAV teams worked directly with the China Association for Disaster and Emergency Response Medicine. Given the dense rubble and vegetation in the disaster affected region of Ludian County, ground surveys were particularly challenging to carry out. The UAVs provided disaster responders with an unimpeded bird's eye view of the damage, helping them prioritize their search and rescue efforts. China has rapidly developed UAV use in recent years, and it helped save time and money while providing highly reliable data. Moreover, multiple UAVs working in groups presents the opportunity for new operational paradigms.

An UAV swarm is a group of vehicles that work together, communicating with each other and assisting other members of the swarm in tasks to accomplish goals. There are many possible applications for UAV swarms, the most immediate could be search and rescue: a swarm could cover a lot of ground quickly and would require only one operator. Another could be exploration: swarms of simple and small vehicles could scan high-risk buildings and sites rapidly, whereas large vehicle cannot. But the challenge is how to control multiple vehicles cooperate automatically to finish a given task. New challenges imposed by intelligent swarms have attracted many researchers since the last decade. New simulation models, command and control mechanisms and simulation tools have been developed to tackle issues in different aspects of the swarm [9].

Control, that is aimed at ensuring the moving object(plant) behaves in a desired manner. Developing a command and control system for coordinating an UAV swarm is more challengeable since the control plant is more complex and meeting with more physical constraints and uncertainties. A computational model of the plant provides a way to test and analyze the performance of the designed controller via simulation. In many cases, testing newly developed control systems in a virtual environment is the only way to guarantee safety. Additionally, the model would allow better repeatability in testing. A good way to model the UAV swarm for testing control scheme is by using a bottom-up modeling approach and using decentralized methods to coordinate vehicles. Although the decentralized approach may require more communication in a low autonomy system, the intelligence is truly distributed, which makes for a more flexible, adaptive and efficient organization. The principles of multi-agent systems have been used in [1, 2, 3] and [10] to issue the control and coordination of swarm.

This paper describes a prototype application for UAV swarm control study by using agent technology. The agents are seen as the enabling technology supporting the fusion of several traditional UAV system areas: guidance and navigation, attitude control, telemetry, etc., in the context of swarm control. Three key sub-models to create a multi-agent system are: agent, agents interaction and environment. In this paper, we introduce an easy-to-use, bottom-up approach to model the vehicles as agents with the consideration of their maneuverability and communication for interaction. Compared with other related works about using multiple agent system for modeling vehicle swarms, our work considered its dynamic characteristic and interaction, the six-degree-of-freedom(6DoF) model is used to represent the physical constraints of UAVs. This simulation system would allow the swarm control system designer to focus on control system design.

The remainder of the paper is organized as follows. In section 2, we discuss some related work on UAV swarm control, model of swarm and swarm intelligent system utilization on UAV related study. Section 3 presents the motivation and the way to model UAVs in principle of multi-agent system. In section 4, we provide the model of communication to achieve interaction purpose. Then the section 5 presents results of a case study to demonstrate an example use of our approach on UAV cooperative study. Conclusions and future work are given in Section 6.

2 Related work

Traditional modeling techniques tended to focus on the mathematical models based on partial differential equations and accurate models, while a vast majority of mathematical models are not solvable analytically, and thus approximate methods and numerical methods are the alternatives[13]. It is hard to say which is better under all cases, proper combination of mathematical and computational model may bring more conveniences in the process of design and development. Over the past two decades, swarm intelligence based computational algorithms for optimization have been very active, there are also considerable works on the merge of multi-agent system and UAVs. Concerning use of agent for studying swarm of UAVs, Gaudiano et al. in [7] proposed an agent-based model and several decentralized strategies for swarm control. Their results show that even some fairly simple swarm control strategies based on local communication can yield satisfactory results on search or suppression missions. Their work demonstrated the feasibility of modeling UAVs as an self-organized agent towards swarm control and coordination study. Unfortunately, in their simulation tools, they consider vehicle as a mass point model with simple constraint and flying in a two dimensional plane. Whereas a flying UAV has many physical constraints, a six-degree-of-free model can better represent these constraints. Furthermore, if consider the flying height degree of an UAV rather than a 2D plane, there exist more ways to avoid collision and may express more scalability and robustness.

In the process of developing intelligent autonomous agents for UAV swarm control, according to the study of R. Ryan et al.[9] , toward the complexity arise from controlling a swarm intelligent system, one solution is decomposing the macro-level emergent behavior into the control of agent-level parameters. Whereas, one of the principal preconditions for this decomposition is that the agents must be self-organized and coordinate in a decentralized manner. Thus, it is necessary to determine the level of autonomy. Clough et al.[5] developed a metrics in terms of autonomous control levels(ACL), which was pioneered by researchers in the Air Force Research Laboratory's Air Vehicles Directorate charged with developing autonomous air vehicles, to determine an UAV's autonomy. Their ACL metrics include eleven levels from zero to ten, level zero represents remotely controlled vehicles and level 10 stands for human-like vehicles. The metrics have been used successfully at the Air Force Research Laboratory in developing plans and programs in autonomous UAV control research. Their work provides a progressive way to study swarm intelligent UAV system from a point view of autonomous agent.

Chopra et al [4] examined a new formulation which views the multi-agent coordination and synchronization from an input-output perspective. An interconnection graph was used to describe agents information exchange over a network. Thus the stability of the multi-agent system was provided by using Lyapunov Krasovskii theorems. In addition, they provided synchronization results for both fixed and switching graphs when the graph topology is not constant, synchronization with time constant and bounded communication delay in the network was also provided. Their work provides one solution to simplify the complexity of a swarm (look the interconnected UAVs as a whole) to design the macro-level swarm behavior control scheme, but it may lack the ability to concern the behavior constraint and uncertainty of each UAV.

Communication among vehicles is one of the most challenging design issues for collaborative multi-UAV systems. Bekmezci et al. made a survey in UAV-to-UAV communication related publications in article [8]. They concluded that if all UAVs are directly connected to an infrastructure, such as a ground base or a satellite, communication between UAVs can be realized. However, this infrastructure based communication architecture restricts the capabilities of the multi-UAV systems. The authors formally defined Flying Ad-hoc Network (FANET) and present several FANET application scenarios. Several existing FANET test beds and simulators are also presented. Their work recognized the importance of communication study among the collaborative UAVs in swarm.

3 Agent model of UAV swarm

3.1 Motivation of modeling UAV as autonomous agent

Multi-agent systems are systems composed of multiple interacting computing elements, known as agents. The agents in a multi-agent system have three important characteristics[12]: **Autonomy**, the agents are at least partially independent, self-aware, autonomous. The metric to define the autonomy level is given in article [5]. **Local views**, no agent has a full global view of the system, or the system is too complex for an agent to make practical use of such knowledge. **Decentralization**, there is no designated controlling agent (or the system is effectively reduced to a monolithic system). In order to take advantage of the decentralized characteristic of the

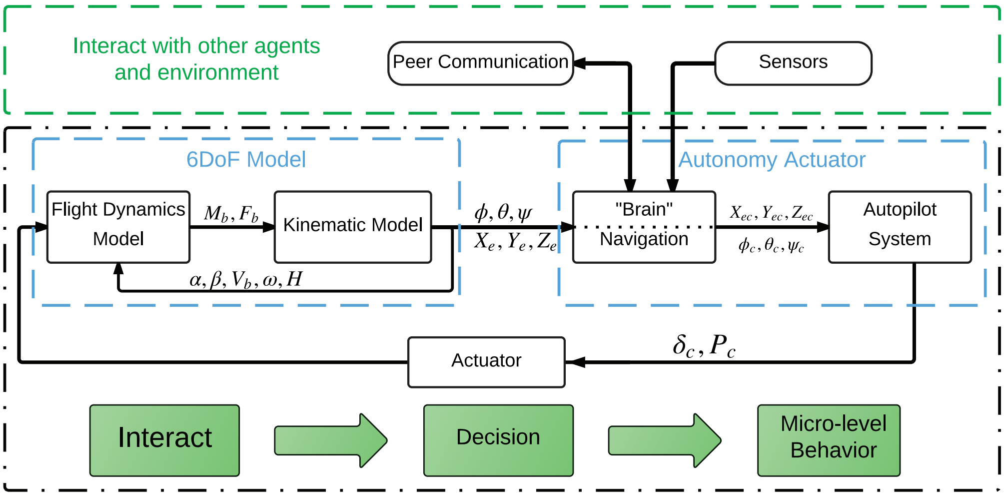


Figure 1: Model an unmanned aerial vehicle as autonomous agent. The sensors and communication devices give it possible to interact with companions and environment. The flight dynamic model reflects constraints and uncertainties.

multi-agent system, the agent should be given some degree of autonomy. When talking about autonomy, we mean the agent can collect information by interacting with other agents or the environment they are in, then make decision according to these information. From the point view of one UAV, outlined in Figure 1, UAVs collect information from other vehicles and the environment, the decisions include special movements, period of trajectory planned etc. Then the navigation system transfer the behavior, position or orientation, to control command for autopilot to achieve. This mechanism is quite different with a living body because the behavior of an flying vehicle contain many uncertainties and constraints, for instance the fixed-wing vehicles must keep a minimum velocity to get enough lift force, their maneuverability is affected by many flight state variables and structure. It is difficult to model these uncertainties and constraints in “if-then” statement. Fortunately, when look back to the design of a single UAV, the mathematica model can represent most of the constraints, and uncertainties can be modeled as stochastic processes. Thus, we can use the mathematic model of UAV to perform their decisions in order to accomplish behaviors, the system which provides intelligence to UAV will be connected with the navigation system.

This section will describe the mathematic model of an UAV from point view of autonomous agent. The equations of motion for a flight vehicle are written in a body-fixed coordinate system $Ox_by_bz_b$ rigidly connected with the moving UAV, with the origin point in the center of gravity. The x-axis lies in the symmetry plane of the vehicle and points forward; the z-axis lies in the symmetry plane of the vehicle, perpendicular to the x-axis, and points down; the y-axis is perpendicular to the symmetry plane of the vehicle and points out the right wing(right-handed). Another reference system is earth-fixed $Ox_ey_ez_e$, the origin O is at an arbitrary location on the ground(e.g. launching point). The x_e-axis is directed North, z_e axis points towards the ground and y_e-axis can be determined by using the right-hand rule.

3.2 Flight Dynamic Model of UAV

The dynamical model of UAV forms the heart of its simulation. It can represent the complex relationship between flight state and constraint, uncertainty. The inputs of flight dynamic submodel include all the flight state variables in given level of detail, outputs are force and moment applied on body. Due to the complexity of a flying air vehicle, it is impossible to consider all the force and moment applied on the body. For lack of space, we only present the main methods for calculating the force and moment on a flying fixed-wing air vehicle. A detailed mathematic model of a fixed-wing aircraft can be found in [6, 11].

The external force applied on flying vehicle include aerodynamic force $F^b_{aero} = \begin{bmatrix} X & Y & Z \end{bmatrix}^T$, gravitational acceleration $F^e_g = \begin{bmatrix} 0 & 0 & mg_0 \end{bmatrix}^T$ and propulsive force P provided by engine. The superscript e and b indicate that the force are given in the $Ox_ey_ez_e$ and $Ox_by_bz_b$ reference system separately. As the point at which the aerodynamic force applied is not in the center of gravity, which will cause external moment $M^b_{aero} = \begin{bmatrix} M_{xb} & M_{yb} & M_{zb} \end{bmatrix}^T$ on the vehicles. F^b_{aero} and M^b_{aero} can be calculated by the given Formula (1).

$$F^b_{aero} = \begin{bmatrix} C_x \\ C_y \\ C_z \end{bmatrix} qS, \quad M^b_{aero} = \begin{bmatrix} m_x \\ m_y \\ m_z \end{bmatrix} qSL, \quad q = \frac{1}{2}\rho V^2 \tag{1}$$

Where, the $\begin{bmatrix} C_x & C_y & C_z \end{bmatrix}^T$ and $\begin{bmatrix} m_x & m_y & m_z \end{bmatrix}^T$ are aerodynamic force and moment coefficient respectively. ρ is the air density, V is the velocity of vehicle and L is the chord length.

Since the direction of P is parallel with Ox_b, the resultant in system $Ox_by_bz_b$ can be calculated by Formula (2).

$$\begin{bmatrix} F_{xb} \\ F_{yb} \\ F_{zb} \end{bmatrix} = mg_0 \begin{bmatrix} -\sin\theta \\ \cos\theta\sin\phi \\ \cos\theta\cos\phi \end{bmatrix} + \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} + \begin{bmatrix} P \\ 0 \\ 0 \end{bmatrix} \tag{2}$$

Given the foregoing, the problem transformed to calculate the coefficients under current flight state. One of the solutions to calculate these coefficients is by using the vehicle's state and control deflections as variables to look-up values from the aerodynamic tables. During the look-up process, interpolation is used for states and deflections not found in the tables. We take the lift coefficient computation as an example, C_z is mainly determined by angle of attack α, velocity V and horizontal tailplane δ_z. Since C_z increases almost linearly with δ_z and α until the stall angle is reached. The wing should never work in this zone where the C_z decreases importantly which makes the airplane loosing altitude very rapidly. We can use the simplified Formula (3) to calculate C_z.

$$C_z = f\left(V, \alpha, \delta_y\right) = C_{z_0} + C_z^{\alpha} \cdot \alpha + C_z^{\delta_y} \cdot \delta_y \tag{3}$$

Where, C_{z0} is the lift coefficient when both α and δ_z are equal to zero(the zero lift coefficient). C_z^{α} and $C_z^{\delta_y}$ are related with velocity, write as: $C_z^{\alpha} = f\left(V\right)$, $C_z^{\alpha} = f^{'}\left(V\right)$. These relationships can be given as a look-up table got through some wind tunnel tests or computational fluid dynamics(CFD) software. Table 1 lists all the parameters needed to define the flight dynamic character of an UAV.

Table 1: List of aerodynamic data needed to model an UAV

Notation	Definition
m, I	The mass and moment of inertia of the rigid body.
S	Sum of wing area.
L	The chord length.
$\boldsymbol{C}_{x,y,z}^{\delta_z}$-$V$	The drag/side/lift force coefficient derivative due to corresponding horizontal tailplane to velocity.
$\boldsymbol{C}_{x,y,z}^{\alpha}$-$V$	The drag/side/lift force coefficient derivative due to angle of attack to velocity.
$\boldsymbol{C}_{(x,y,z)_0}$	The zero drag/side/lift force coefficient.
$\boldsymbol{m}_{x,y,z}^{\delta_z}$-$V$	The roll/pitch/yaw moment coefficient derivative due to corresponding horizontal tailplane to velocity.
$\boldsymbol{m}_{x,y,z}^{\alpha}$-$V$	The roll/pitch/yaw coefficient derivative due to angle of attack to velocity.
$\boldsymbol{m}_{(x,y,z)_0}$	The zero roll/pitch/yaw moment coefficient.

3.3 Kinematic Model

The Section 3.2 gives the way to compute force and moment apply on vehicle according to current flight state. In this section, we use Euler angle representation to implement the six-degrees-of-freedom equations of motion. The motion of a unmanned aircraft vehicle is examined in the reference system $Ox_by_bz_b$. The inputs to the kinematic model include: force $\begin{bmatrix} F_{xb} & F_{yb} & F_{zb} \end{bmatrix}^T$ and moment $\begin{bmatrix} M_{xb} & M_{yb} & M_{zb} \end{bmatrix}^T$, both should be given in the body-fixed frame. The outputs include: position $\begin{bmatrix} x_e & y_e & z_e \end{bmatrix}^T$ and velocity V_e in earth-fixed reference frame, angle of attack α, sideslip β, Euler angles $\begin{bmatrix} \varphi & \theta & \psi \end{bmatrix}^T$ and the body-fixed angular velocity vector ω.

$$\dot{V_b} = \frac{1}{m}\begin{bmatrix} F_{xb} \\ F_{yb} \\ F_{zb} \end{bmatrix} + V_b \times \omega, \quad \omega = \begin{bmatrix} p \\ q \\ r \end{bmatrix} \tag{4}$$

Equation (4) gives the accelerated velocity in the system $Ox_by_bz_b$. The linear velocity $\begin{bmatrix} V_{xb} & V_{yb} & V_{zb} \end{bmatrix}^T$ in the system $Ox_by_bz_b$ can be calculated through integration. Then the velocity in system $Ox_ey_ez_e$ was calculated by multiply with a ZYX rotation order direction cosine matrix(DCM), i.ie, $V_e = M_{DCM} * V_b$. Moving on from here, the location of UAV ($\begin{bmatrix} x_e & y_e & z_e \end{bmatrix}^T$) in the system $Ox_ey_ez_e$ is calculated by integrating velocity V_e.

As for angular rotation, Equation (5) gives the body-fixed accelerated angular velocity $\dot{\omega}$, then the body-fixed angular velocity vector ω can be updated.

$$\dot{\omega} = I^{-1}\left(\begin{bmatrix} M_{xb} \\ M_{yb} \\ M_{zb} \end{bmatrix} + (I\omega)\times\omega\right), \quad I = \begin{pmatrix} I_{xx} & -I_{xy} & -I_{xz} \\ -I_{yx} & I_{yy} & -I_{yz} \\ -I_{zx} & -I_{zy} & I_{zz} \end{pmatrix} \tag{5}$$

The relationship between the body-fixed angular velocity vector, $\begin{bmatrix} p & q & r \end{bmatrix}^T$, and the rate of change of the Euler angles $\begin{bmatrix} \dot{\varphi} & \dot{\theta} & \dot{\psi} \end{bmatrix}^T$, can be determined by resolving the Euler rates into the body-fixed coordinate frame [6, 11] as shown in Formula (6).

$$\begin{bmatrix} p \\ q \\ r \end{bmatrix} = \begin{bmatrix} \dot{\varphi} \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\varphi & \sin\varphi \\ 0 & -\sin\varphi & \cos\varphi \end{bmatrix} \begin{bmatrix} 0 \\ \dot{\theta} \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\varphi & \sin\varphi \\ 0 & -\sin\varphi & \cos\varphi \end{bmatrix} \begin{bmatrix} \cos\theta & 0 & -\sin\theta \\ 0 & 1 & 0 \\ \sin\theta & 0 & \cos\theta \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ \dot{\psi} \end{bmatrix} = J^{-1} \begin{bmatrix} \dot{\varphi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} \tag{6}$$

Inverting J gives the required relationship to determine the Euler rate vector from the body-fixed angular velocity.

$$\begin{bmatrix} \dot{\varphi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} = J \begin{bmatrix} p \\ q \\ r \end{bmatrix} = \begin{bmatrix} 1 & (\sin\varphi\tan\theta) & (\cos\varphi\tan\theta) \\ 0 & \cos\varphi & -\sin\varphi \\ 0 & (\sin\varphi\sec\theta) & (\cos\varphi\sec\theta) \end{bmatrix} \begin{bmatrix} p \\ q \\ r \end{bmatrix} \tag{7}$$

Given the foregoing, the Euler angle can be updated through integrating of $\begin{bmatrix} \dot{\varphi} & \dot{\theta} & \dot{\psi} \end{bmatrix}^T$ separately.

Finally, in calm weather the angle of attack α and sideslip β are expressed by the formulas (8) according to the definition of α and β.

$$\alpha = \arctan\frac{V_{zb}}{V_{xb}}, \quad \beta = \arcsin\frac{V_{by}}{\sqrt{{V_{xb}}^2 + {V_{yb}}^2 + {V_{zb}}^2}} \tag{8}$$

4 Interaction amongst UAVs

Multi-agent coordination is the key to multi-agent problem solving. In order to get information for deciding which actions to take, communication is crucial for agents to coordinate properly. Since UAVs move quickly and flexibly, it is difficult to communicate by using wire. Even using wireless techniques, the flying attitude and the speed of UAV should be considered. So, the communication should be carefully considered in an agent level when developing a swarm control system. This section presents the model of communication amongst UAVs with the purpose of analyzing and optimizing UAV communication strategies.

From point view of wireless signal coverage, we implemented two types of communication in terms of latency, coverage and power consumption to achieve interaction purpose among agents: *direct*, UAVs can communicate directly without base station support but with a constrained coverage; *in-direct*, communicate via some ground supported base station or moving vehicles supported base station without distance restriction. The *direct* communication, such as WiFi, Bluetooth and ZigBee, their advantages include low power consumption, less latency and free of charge. Long distance *in-direct* communication, for instance, GSM and satellite, although they can provide big coverage, usually consume more power, cost money and with high latency.

In application level, we introduced three communication types, i.e., *broadcast*: an agent share its current state to a set of agents; *query*: an agent send a message to a set of agents to request their states; *sync*: an agent (e.g. group leader) send a sync request message to a group of agents, then all the agents who receive the sync request will broadcast their current state to other group members. Through this, the control mechanism designer can design policies to properly choose *direct* or *in-direct* communication media for passing messages. For example, to know the state of all UAVs in the coverage of *direct* communication device, just need to send a query message to all the UAVs through direct communication way, only those who are currently in the direct communication range could receive this message and reply their state.

As for implementation, we implemented a message switch layer(MSL) work in an observer role(not exist in real situation, only for implementation, all information about simulation world is accessible by observer), all the communication amongst UAVs will pass through this layer and MSL will record all these messages for post-simulation analysis. This provides a flexible way for control mechanism designer to optimize the communication policies in micro-level behavior.

5 Experiments and Discussion

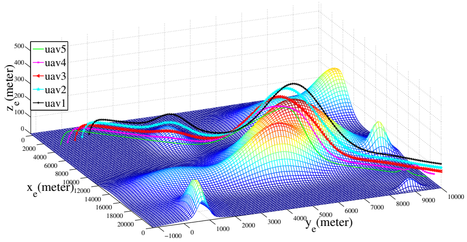
In this section we present a simple case study to demonstrate the possible use of the presented approach. The proof-of-concept simulator has been implemented by using Netlogo3D. The task is to control a swarm of five UAVs, the mission of swarms is to "scan"(e.g., searching survival) a mountain area of size $10 \times 20km^2$ on a preset height(100 meters over ground). All the five UAVs cooperate by forming in a horizontal line perpendicular to ground speed direction, the distance between two neighboring UAVs should be kept as 500 meters and a leader was set in the center to direct the formation(*broadcast* its state actively). All the vehicles fly with their curing speed($35m/s$) to save power consumption. The physical parameter of the vehicles are from a commercial available Tower Trainer 40 aircraft. To make it easier to implement in Netlogo3D, the dynamic process was described by means of an inertial unit of the first order and ground level height was achieved by a PID controller. Its navigation system receive messages about leader states from the leader and ground height from its sensors. The distance error between neighbor vehicles and the height error to the ground will be used to generate tailplane control command δ_{zc} and thrust command P_c to achieve micro-level behavior as drawn in Figure 3.

As for the simulation environment, an exponential function, as in (9), is introduced to emulate mountains which are the main threats of the UAVs in this experiment.

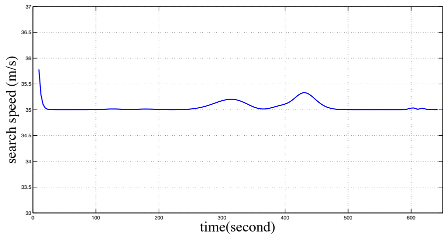
$$z(x,y) = \sum_{i=1}^{n} h_i * exp\left(-\left(\frac{x - c_{x_i}}{g_{x_i}}\right)^2 - \left(\frac{y - c_{y_i}}{g_{y_i}}\right)^2\right) \tag{9}$$

This function gives altitude of the given coordinate (x, y) in the simulated terrain. Where, h_i controls height of peak i; c_{x_i} and c_{y_i} mark central position of peak i; g_{x_i} and g_{y_i} control peak gradient in x and y orientation respectively. With this model, we created an area with 15 mountains, the swarm will "scan" this area by a line formation with constant speed at a preset ground height. Selected macro-level behavior emerge from agent-level behavior are shown in Figure 2 and 3. One of the constraints reflected by 6DoF mathematic model was shown in Figure 3b. It allows to study how system level properties emerge from the adaptive behavior of individuals as well as how, on the other hand, the system affects individuals.

As we consider the collaborative UAVs as autonomous agents, although the designed scheme is to control the macro-level emergent behavior of swarm to meet the application objective, it is easy to break the overall mission into agent-level behavior control. With this, we can analyze the execution of the control algorithm in micro-level(error and control command). This individual behavior provides detailed information to analyze the behavior achievement of controller. This

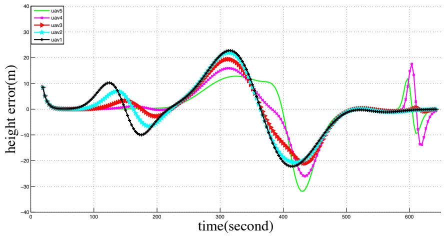


(a) 3D View of UAV swarm trajectory

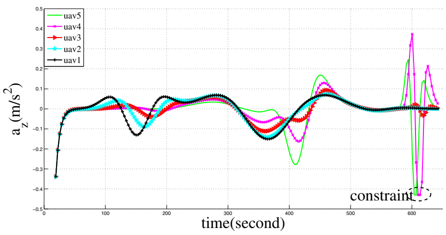


(b) Search speed of UAV swarm

Figure 2: Swarm trajectory and search speed (macro-level behavior).



(a) Height error



(b) UAVs' normal acceleration (meet constraint)

Figure 3: UAVs' height error and normal acceleration (micro-level behavior).

approach alleviate control problems arising from the non-linearity relationship between the agent-level control behavior and application-level emergent behavior.

6 Conclusions and Future work

Instead of developing and operating one large vehicle, using a group of small UAVs has many advantages. Whereas, a flying vehicle has many uncertainties and constraints that are difficult to model through a "If...Then...Else" statement. The complexity of swarm arises the difficulty to analyze and evaluate the control and coordination mechanism. This paper presented the idea to model an UAV swarm as a multi-agent system. A six-degree-of-freedom mathematic model was used in order to fully represent constraints and uncertainties of flying vehicles. It combines the traditional calculus based mathematical methods with computational techniques. The model we presented can be used for developing and analyzing the global coordination control algorithms, examining effects of communication difficulties on coordination control scheme from an individual level response. It simplifies the modeling process without missing agent behavior constraint character.

This work is a part of a longterm project about intelligent UAV swarm application. As the future work, in one side, although the prototype proved the possibility of modeling UAVs as agents in terms of the multi-agent system principle, in a Netlogo3D world the number of patches grows very quickly that slow the model down or even cause NetLogo to run out of memory. For this reason, we plan to implement our next version by using Go programming language, because it supports concurrency and channel communication between its light process(one process will be used to execute the model of one UAV). It seems to be an interesting framework for implementing multi-agent systems. Currently, we only considered the fixed-wing vehicle, whereas, rotary-wing, such as quadcopter is also widely used in some application. So, in another side, we will construct the model of quadcopter in order to provide the ability of building heterogeneous UAV swarm.

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