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THEORY

Direct Data Driven Control for UAVs Formation Dynamic Network

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ABSTRACT This new paper applies the novel direct data driven control into UAVs formation dynamic network and designs the distributed controller for each UAV, while guaranteeing the desired flight performance. Firstly, a new control architecture is constructed as an unified framework for UAV task implementation, including the management layer, functional layer and physical layer together. Secondly, we explain one special dynamic network, i.e. network modules, exist in above control architecture, and the process about how to operate these network modules in described in detail. Thirdly, after introducing the idea of distributed control and the dynamic network system, our main contribution concern on how to apply direct data driven control to design these distributed controllers for all UAVs respectively. Furthermore, the detailed derivations and one improvement are combined to complete our own proposed theoretical results. Finally, one simulation example confirms above theories.

INDEX TERMS UAVs formation, dynamic network, direct data driven control, model reference performance.

I. INTRODUCTION

Without control systems there could be no manufacturing, no vehicles, no computers, no regulated environment-in short, no technology. Control systems are what make machines, in the broadest sense of the term, function as intended. Control systems are most often based on the principle of feedback, whereby the signal to be controlled is compared to a desired reference signal and the discrepancy used to compute corrective control action. The process of designing a control system generally involves many steps. A typical scenario is as follows. (1) Study the system to be controlled and decide what types of sensors and actuators will be used and where they will be placed; (2) Model the resulting system to be controlled;(3) Simplify the model if necessary so that it is tractable;(4) Analyze the resulting model and determine its properties; (5) Decide on performance specifications; (6) Decide on the type of controller to be used; (7)Design a controller to meet the performance, if possible, if not, modify the performance or generalized the type of controller sought; (8) Simulate the resulting control system, either on a computer or in a pilot plant; (9) Repeat from step 1 if necessary; (10) Choose hardware and software and implement the controller; (11) Tune the controller on line if necessary.

Observing the controller design problem in open loop or closed loop situation, i.e. above described feedback situation, methods for the design of controllers on the basis of data are divided into two categories, (1) model-based control and (2) direct data driven control. For model based control, firstly a plant model is identified on virtue of data and consequently a control design is performed on this plant model. The problem of identifying a mathematical model for the latter controller design is considered in the field of identification for control, it means the identified plant model will influence the best control performance. In direct data driven control, the plant modeling step is avoided, so a controller is synthesized directly from data. Typical advantages of direct data driven control are that no loss of data can occur due to under modeling of the plant and the order of the controller can be fixed. Generally, model based control includes two main steps,i.e. system modeling and controller design. But direct data driven control strategy designs the unknown

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controller without any information about that unknown plant, i.e. avoiding the system modeling process for that unknown plant. Formally speaking, direct data driven control extracts the useful information of the controller from the collected data directly through some statistical methods,which need lots of data. This requirement of data tolerable in today's information era.

Although the design of controllers from data directly has been extensively studied in the literature. However most of the theoretical results apply only to isolated systems or small scale systems, but the dynamic network structure is not still taken into account. Dynamic network exists all over our lives, for example, think about any device around you that is electrical or mechanical. Likely, this device consists of several interconnected components or is interconnected with one or multiple other devices. In the current era of technology, it is hard to imagine a world with complex technological systems that enhance our society. Be it the power generators feeding the electricity grid, irrigation systems that serve the demand for water in growing crops, or our mobile phone that allows us to connect to any other device connected to the internet.UAV formation is a whole system, composing of multi UAV units. From the point of command and control, it concerns on the combat effectiveness of UAV formation, that is the emergence by the cooperation of multi UAVs. Within UAVs formation, each UAV is regarded as a non-separable description object, and the information interaction among the units are analyzed to describe each UAV unit through the entity behavior. When to analyze the motion mechanism of each UAV unit and the latter task planning or allocation, it is obviously not enough to regard UAV unit as an indivisible, but a whole system. Then we must analyze the function modules of all UAVs in detail from the point of function realization and the information interaction among them, so it is better to understand the working principle of each UAV and construct the explicit module of UAV unit. If we abandon the research on each separable UAV unit, but turn to consider UAV formation as a whole system, it corresponds to our named UAVs formation dynamic network, due to the dynamic network exists among the information interaction.

Although few research exists about UAVs formation dynamic network, but research about direct data driven control from the theoretical point are very mature. AN exhaustive survey on data driven control methods,both direct and indirect, is provided in [1]. One kind of special direct data driven control- virtual reference feedback tuning [2] is a one shot method for designing a controller directly on the basis of data. In reference [3], a model-reference control problem is essentially reformulate into a system identification problem, through the generation of a virtual closed loop experiment. Iterative feedback tuning, proposed in [4], shares the nice property of being direct, i.e.e no model is needed in the procedure. A distinguishing feature of direct data driven control is that it is iterative by design, where a gradient estimation of the control criterion is performed at each iterative to tune the controller parameter [5]. Optimal controller identification [6] also solves a model-reference control problem, by embedding the control design problem within the prediction error identification of an optimal controller [7]. Reference [8] extends this method for the identification of multi input multi output systems. Other state of art methods for direct data driven control are correlation based tuning [9]. A recent trend in direct data based system analysis and control originates from Willerns' fundamental lemma [10]. Applications include data based predictive control [11], the data based parametrization of stabilizing controllers and robust data state feedback design with noisy data [12].

There are lots of research on UAV, for example, UAV control, UAV target detection, UAV system identification, UAV formation, etc. More specifically, in UAV system identification, the total number of observations, use to extract the intrinsic principle of the considered system, is the sample size [13]. In case of the number of observations be more exceed this sample size, then the input is persistent excitation, while the identification model satisfies the expected accuracy. From the knowledge of system identification theory, the situation with observed disturbance or noise in the output corresponds to the robust system identification [14], which being also extended to robust optimal control. When using the probabilistic or statistical inference in system identification theory in [15] to measure the asymptotic accuracy about the final identification model. Furthermore in recent years, risk sensitive theory and reinforce learning are all introduced in system theory and advanced control theory [16] and [17], i.e. the risk decision and limitations of policies were considered during the whole process of identification and controller design. Then the final identification system or plant is more realistic then classical theoretical result. From these ongoing subjects about applying risk theory, dynamic programming and probabilistic limitation for system identification and control theory, we are thinking to extend graph theory and topology to system identification. More specifically, the second step-model structure choice is related with graph theory, i.e. the chosen model is constructed as one network system, being formulated as graph theory. System identification theory is not only for our considered aircraft system identification, but also for robot system identification in [18].

As lots of identification processed are transformed into their corresponding constrain optimization problems, so some existed optimization results can be applied directly, for example, convex optimization [19], scenario optimization [20], and scenario robust control [21], etc. Consider the last step for system identification-model validation, some nice properties are satisfied for the final identification model or designed controller, such as controllability, stochastic chance constraints, robustness and nonlinearity [22]. The goal of experiment design is to maximize the information content in the data, subject to practical constraints, for example [23], limits on input or output amplitude to ensure that a linear model structure can be used to estimate

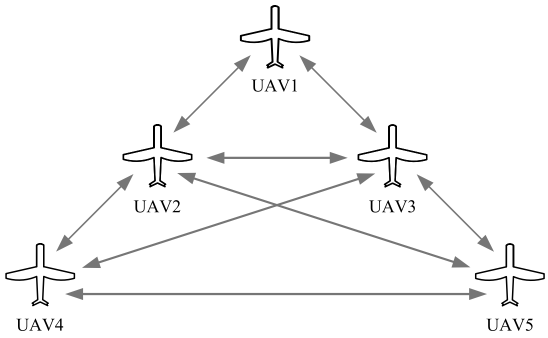

FIGURE 1. **UAVs formation dynamic network.**

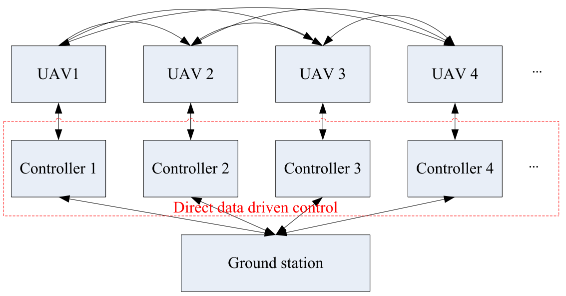

FIGURE 2. **Control framework.**

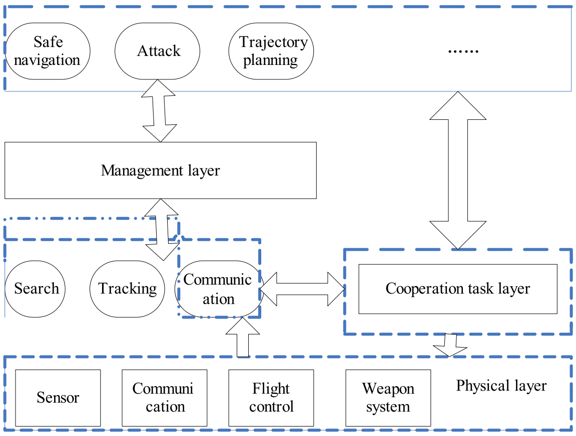

FIGURE 3. **UAV cooperation architecture.**

parameters from the measured data. Reference [24] studies the time-varying formation tracking problem for linear multiagent systems, where followers reach a preset TVF when tracking the leader's state. The time-varying output bipartite formation containment problem for linear multiagent systems under directed graphs is an important problem, reference [25] investigates two kinds of TVOBFC problems for heterogeneous linear MASs under signed digraphs by event-triggered communication.

This new paper applies the existed direct data driven control into UAVs formation dynamic network and designs the distributed controller for each UAV, while guaranteeing the desired flight trajectory and goal in this complex formation flight. More specifically, assume five UAVs fly in the formation to achieve the same battle mission, plotting in Figure 1. The ground station receives the signal from these flying UAVs and sends the command to them. Each UAV, flying in this formation, exchanges the useful information to other UAVs and the ground station, i.e. the information interactions exist among UAVs and the ground station. One efficient way to describe these information interactions depends on our called formation dynamic network, i.e. the communication links constitute one dynamic network for Figure 1.

Consider one interesting controller design problem within above UAVs formation dynamic network, three kinds of control frameworks are always used, i.e.centralized control, decentralized control and distributed control. The detailed differences among these three control frameworks are shown in our paper [26], which points out that the idea of distributed control is to design controller for each UAV, while considering the influences from other adjacent UAVs. Then idea of distribute control is shown in Figure 2, which shows the closed relations among UAVs, controllers and the ground station.

where, in Figure 2, each controller, corresponding to each UAV, is devised by our considered direct data driven control.

The main contribution of this new paper is to design each controller for each UAV in one formation dynamic network by virtue of direct data driven control strategy. But for the completeness, firstly we introduce a new cooperation control architecture to achieve the effective cooperation task, then this new cooperative control architecture corresponds to one UAVs formation dynamic network. It provides an unified structure for various functional modules, such as a physical layer, a functional layer and a management layer. Secondly, for this UAVs formation dynamic network, we consider the distributed controller design problem through our proposed direct data driven control strategy, i.e. each controller is designed from the collected data in detail. Generally, after introducing UAVs formation dynamic network as one new architecture, direct data driven control is proposed to design each distributed controller for each UAV. Furthermore, some considerations and more important aspects about how to apply direct data driven control into this new UAVs formation dynamic network are explained in detail with tou own descriptions and mathematical derivations.

The paper is organized follows. In section II, UAVs formation dynamic network is introduced to be a new cooperation control architecture, being for the task cooperation planning in UAVs formation. The main contribution about applying direct data driven control to design the distributed controller for each UAV in formation is given in section III, where further control analysis is also done for better understanding. Section IV uses some simulation examples to prove our proposed results efficiently. Finally, section V formulates the main conclusions and points our latter work. Generally, this new paper combines the theory and practice together from both points of architecture and controller design problem for UAVs formation.

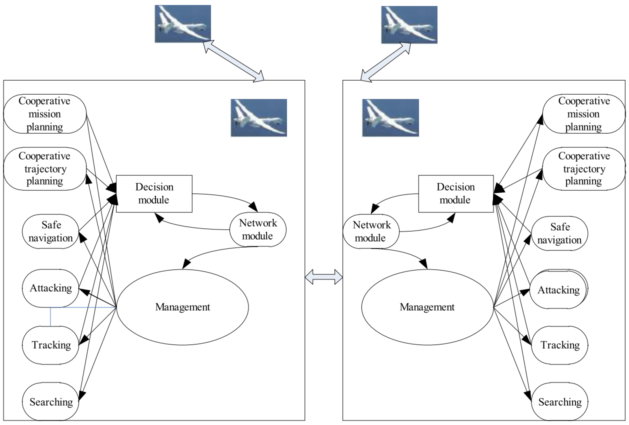

FIGURE 4. Network module for cooperation task planning.

II. UAVs FORMATION DYNAMIC NETWORK

This section is similar to the system description, corresponding to a new architecture as an unified framework for UAV task implementation. And this new architecture includes our mentioned dynamic network.

A. ARCHITECTURE

The design of this new architecture provides efficient support for multi task allocation of UAV. A diagram of this new architecture is plotted in Figure 3, which includes the management, functional and physical layer together.
where, in Figure 3, the lowest physical layer supports the most basic operations among UAV. It mainly includes the bottom control system and other hardware resources, such as sensor, communication system, weapon system etc.

The functional layer in above dotted line box includes all kinds of functional modules, for example safe navigation, collision avoidance, trajectory planning, target search and recognition, target tracking etc. Each functional module corresponds to the special type of each UAV task, and has its own unique system object about state and parameter. The middle task coordination layer can allow different functional sub-modules to cooperate and share with each other. The state and parameter in a functional module can be shared with other functional modules through registering with management layer, which include current information about UAV in different task environment.

B. DYNAMIC NETWORK

That proposed cooperation control architecture is Figure 3 provides an efficient support system for single UAV or multi UAVs formation cooperation task planning. Observing Figure 3 again, the network module of the functional layer can be used directly to ensure that all functional modules cooperate during the communication network. Furthermore, this network module gives the communication service protocol for other sub-modules. Figure 4 shows how the network module among UAVs formation functional modules cooperates with the cooperation control architecture. To realize cooperation, communication requirements are sent to network module through task coordination layer module. The network module processes the sequence of data, then data fusion and data mining algorithms can be implemented to deal with the collected data.

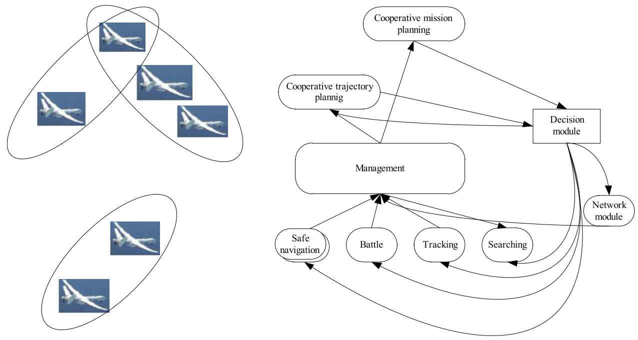

FIGURE 5. Network module for cooperation reconnaissance planning.

Specifically,the received data is sent directly forward to the data receiving buffer of the relevant module in the management layer through the processing of network module. Then the data set processed by network module will be sent to the next UAV along the information flow path in the communication network within the closed loop situation. the network module in UAV functional module can not only has the function of data processing and data transmission, but also support the connectivity of communication network. The connectivity of the communication network can satisfy the communication dynamic characteristics for UAV task planning, plotted in Figure 5.

Compared with other functional modules, the network module sends the control requirements to the task coordination layer, then UAV is controlled according to the network target. Based on this network module, a variety of functional modules on each UAV exist, for example, cooperation task planning, cooperation trajectory planning, attack, tracking and search module, which communicate with their adjacent UAVs, flying in formation. To achieve the sharing of information resources among flying UAVs, our proposed architecture is satisfied to realize the desired control performance.

III. DIRECT DATA DRIVEN CONTROL

From this section, we start to show our contribution about applying the novel direct data driven control into designing the distributed controller for each UAV, flying in the above introduced UAVs formation dynamic network.

A. BACKGROUND

Observing Figure 1 again, assume M UAVs fly in the formation flight, so some communication links or information interactions exist among these M UAVs. Consider the distributed controller design problem for each UAV, we do not neglect the influence from other adjacent UAVs. Combining above introductions about dynamic network and distributed

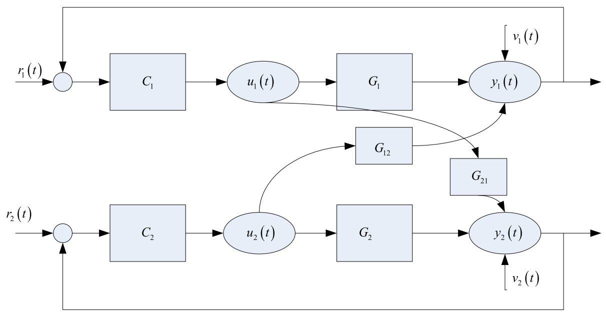

FIGURE 6. Relations between adjacent UAVs.

control, the intrinsic relations between two adjacent UAVs are described in Figure 6.

where, $r_1(t)$ and $r_2(t)$ are two external signals for the first and second UAV respectively. Similarly, $\{u_1(t), u_2(t)\}$ and $\{y_1(t), y_2(t)\}$ correspond to the considered two UAVs' input and output signals. G_1 and G_2 describe the two rational rational functions, C_1 and C_2 are their own distributed controllers, $G_{12}$is the influence on the first UAV, coming from the second UAV, then G_{21} denotes the influence on the second UAV from the first UAV. $\{v_1(t), v_2(t)\}$ are two external noises or disturbances.

More generally, consider *ith* UAV in the formation, its input and output are $\{u_i(t), y_i(t)\}$ at time instant t. Similarly, other physical variables are also defined as $G_i, C_i, G_{ij}, v_i(t), r_i(t)$. The neighbour set of UAV $i \in \{1, 2, \cdots M\}$ is defined as $N_i = \{j \in \{1, 2, \cdots M\} | G_{ij} \neq 0\}$. To each UAV $i \in \{1, 2, \cdots M\}$, we yield a linear discrete time system with dynamic.

$$\begin{aligned} y_i(t) &= G_i u_i(t) + \sum_{j \in N_i} G_{ij} y_j(t) + v_i(t) \\ v_i(t) &= H_i e_i(t), i = 1, 2, \cdots M \end{aligned} \tag{1}$$

The second term $\sum_{j \in N_i} G_{ij} y_j(t)$ means the communication information from other related UAVs. H_i is one transfer function or filter on that unmeasured zero mean white noise process, i.e.

$$\begin{aligned} Ee_i(t)e_j(s) &= 0, for \quad i \neq j \\ Ee_i(t)u_j(s) &= 0, for \quad i \neq j \end{aligned} \tag{2}$$

As M UAVs are considered within the formation, so all output signals for all M UAVs are formulated as that.

$$\begin{aligned} \begin{pmatrix} y_1(t) \\ y_2(t) \\ \vdots \\ y_M(t) \end{pmatrix} &= \begin{pmatrix} G_1 & 0 & \cdots & 0 \\ 0 & G_2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & G_M \end{pmatrix} \begin{pmatrix} u_1(t) \\ u_2(t) \\ \vdots \\ u_M(t) \end{pmatrix} \\ &+ \begin{pmatrix} 0 & G_{12} & \cdots & G_{1M} \\ G_{21} & 0 & \cdots & G_{2M} \\ \vdots & \vdots & \vdots & \vdots \\ G_{M1} & G_{M2} & \cdots & 0 \end{pmatrix} \begin{pmatrix} y_1(t) \\ y_2(t) \\ \vdots \\ y_M(t) \end{pmatrix} \\ &+ \begin{pmatrix} H_1 & 0 & \cdots & 0 \\ 0 & H_2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & H_M \end{pmatrix} \begin{pmatrix} e_1(t) \\ e_2(t) \\ \vdots \\ e_M(t) \end{pmatrix} \end{aligned} \tag{3}$$

by stacking all the variables of above network equation (3) as

$$\begin{aligned} y &= col(y_1(t), y_2(t), \cdots, y_M(t)) \\ u &= col(u_1(t), u_2(t), \cdots, u_M(t)) \\ e &= col(e_1(t), e_2(t), \cdots, e_M(t)) \end{aligned}$$

we write

$$y = Gu + G_I y + He \tag{4}$$

with

$$\begin{aligned} G &= diag(G_1, G_2, \cdots, G_M) \\ H &= diag(H_1, H_2, \cdots, H_M) \\ G_I &= \begin{pmatrix} 0 & G_{12} & \cdots & G_{1M} \\ G_{21} & 0 & \cdots & G_{2M} \\ \vdots & \vdots & \vdots & \vdots \\ G_{M1} & G_{M2} & \cdots & 0 \end{pmatrix} \end{aligned} \tag{5}$$

Then the input-output ($u \rightarrow y$) behavior of above dynamic network is

$$\begin{aligned} (I - G_I)^{-1} y &= Gu + He \\ y &= (I - G_I)^{-1} Gu + (I - G_I)^{-1} He \end{aligned} \tag{6}$$

If $M = 1$, i.e. only one UAV is considered, then $G_{1j} = 0$, $G_I = 0$, and $I - G_I = I$, so above equation (6) is reduced to $y = Gu + He$.

B. CONTROL ANALYSIS

Reformulate equation (1) as that

$$y_i(t) = G_i u_i(t) + \sum_{j \in N_i} G_{ij} y_j(t) + H_i e_i(t) \tag{7}$$

with three kinds of unknown rational transfer functions $\{G_i, G_{ij}, H_i\}$. Its one step ahead predictor for output $y_i(t)$ is given by

$$\begin{aligned} \hat{y}_i(t) &= (1 - H_i^{-1}) y_i(t) \\ &+ H_i^{-1}(G_i u_i(t) + \sum_{j \in N_i} G_{ij} y_j(t)) \end{aligned} \tag{8}$$

The corresponding prediction error $\xi_i(t) = y_i(t) - \hat{y}_i(t)$ is minimized to get the rational transfer functions $\{G_i, G_{ij}, H_i\}$, i.e.

$$\arg\min_{\{G_i, G_{ij}, H_i\}} \frac{1}{N} \sum_{t=1}^{N} \xi_i^2(t) \tag{9}$$

where, N is the total number of observed data.

The process of solving above minimization problem (9) corresponds to closed loop system identification, being seen our previous papers [27] and [28]. But here we do not want to identify these three rational transfer functions $\{G_i, G_{ij}, H_i\}$, as our interesting goal is to design that distributed controller C_i for the *ith* UAV without identifying $\{G_i, G_{ij}, H_i\}$. It is achieved from our proposed direct data driven control strategy.

C. DIRECT DATA DRIVEN CONTROL

Direct data driven control is to apply the observed data to design the controller or give some hints. Specifically, for each UAV, assume the expected or designed trajectory be given as

$$y_i(t) = M_i r_i(t) \tag{10}$$

with the external input $r_i(t)$ and expected transfer function M_i. From Figure 1, it holds that

$$u_i(t) = C_i(r_i(t) - y_i(t)) \tag{11}$$

Substituting equation (11) into (1), we have

$$\begin{aligned} y_i(t) &= G_i u_i(t) + \sum_{j \in N_i} G_{ij} y_j(t) + H_i e_i(t) \\ &= G_i C_i(r_i(t) - y_i(t)) + \sum_{j \in N_i} G_{ij} y_j(t) + H_i e_i(t) \end{aligned}$$

$$\begin{aligned} [I + G_i C_i] y_i(t) &= G_i C_i r_i(t) \\ &\quad + \sum_{j \in N_i} G_{ij} y_j(t) + H_i e_i(t) \end{aligned} \tag{12}$$

i.e.

$$\begin{aligned} y_i(t) &= [I + G_i C_i]^{-1} G_i C_i r_i(t) \\ &\quad + [I + G_i C_i]^{-1} (\sum_{j \in N_i} G_{ij} y_j(t) + H_i e_i(t)) \end{aligned} \tag{13}$$

Comparing equation (10) and (13), we see the transfer function from the external input $r_i(t)$ to output $y_i(t)$ for each *ith* UAV must be the same, i.e.

$$[I + G_i C_i]^{-1} G_i C_i \to M_i \tag{14}$$

so that distributed controller C_i can be solved through minimizing the following cost function.

$$\arg\min_{\{C_i\}} \|[I + G_i C_i]^{-1} G_i C_i - M_i\|^2 \tag{15}$$

where, $\|.\|$ means Euclidean norm.

An easy way to yield one explicit form for the distributed controller C_i is to take the partial derivative with respect to C_i and set the derivative equal to zero, then we have

$$\begin{aligned} &[\frac{G_i C_i}{1 + G_i C_i} - M_i] \frac{G_i}{(1 + G_i C_i)^2} = 0 \\ &1 - \frac{1}{1 + G_i C_i} - M_i = 0 \end{aligned} \tag{16}$$

as a straight forward calculation shows

$$\begin{aligned} G_i C_i &= 1 - \frac{1}{1 - M_i} \\ C_i &= \frac{M_i}{(M_i - 1) G_i} \end{aligned} \tag{17}$$

Then above form is the distributed controller, which guarantees those two transfer functions be same with each other.

Comment: The obtained distributed controller in equation (17) is dependent of transfer function M_i and G_i. Although that expected transfer function M_i is given and known, but transfer function G_i is unknown, so equation (17) is useful on basis of the given transfer function M_i and the identified plant G_i, being identified in priori. The description about the obtained distributed controller in equation (17) corresponds to the model based control. To avoid $G_i$in the derivation of distributed controller C_i, one improvement is proposed to neglect the existence of that unknown plant G_i.

D. ONE IMPROVEMENT

To delete the unknown plant G_i in equation (7), we see Figure 6 again, the left side of the unknown distributed controller C_i is that.

$$\begin{aligned} y_i(t) &= M_i r_i(t) \\ r_i(t) - y_i(t) &= r_i(t) - M_i r_i(t) = (1 - M_i) r_i(t) \end{aligned} \tag{18}$$

so the right side of the unknown distributed controller C_i is that.

$$u_i(t) = C_i(r_i(t) - y_i(t)) = C_i(1 - M_i) r_i(t) \tag{19}$$

From the expected equity $y_i(t) = M_i r_i(t)$, we get $r_i(t) = M_i^{-1} y_i(t)$. Substituting it into equation (19), we have

$$u_i(t) = C_i(1 - M_i) M_i^{-1} y_i(t) = C_i(M_i^{-1} - 1) y_i(t) \tag{20}$$

Both sides of the unknown distributed controller C_i are input-output signal $\{u_i(t), C_i(M_i^{-1} - 1) y_i(t)\}$. As a pair of data $\{u_i(t), y_i(t)\}$ can be measured in priori, so they are known,and also M_i^{-1} is given, but only that distributed controller C_i is unknown. From our explanation, the distributed controller C_i is solved from the latter minimization problem.

$$\arg\min_{\{C_i\}} \frac{1}{N} \sum_{t=1}^{N} [u_i(t) - C_i(M_i^{-1} - 1) y_i(t)]^2 \tag{21}$$

with the given M_i and collected input-output pair $\{u_i(t), y_i(t)\}_{t=1}^{N}$. By differentiating with respect to C_i and by setting the derivative equal to zero, it holds that

$$\begin{aligned} &\frac{2}{N} \sum_{t=1}^{N} [u_i(t) - C_i(1 - M_i) y_i(t)](1 - M_i) y_i(t) = 0 \\ &\sum_{t=1}^{N} u_i(t) y_i(t) = C_i(1 - M_i) \sum_{t=1}^{N} y_i(t) y_i(t) \\ &\phi_{u_i y_i}(w) = C_i(1 - M_i) \phi_{y_i}(w) \end{aligned} \tag{22}$$

with two power spectrums $\phi_{u_i y_i}(w)$ and $\phi_{y_i}(w)$, i.e,

$$\begin{aligned} \phi_{u_i y_i}(w) &= E u_i(t) y_i(t) \\ \phi_{y_i}(w) &= E y_i(t) y_i(t) \end{aligned} \tag{23}$$

From equation (22), the final distributed controller C_i is given as.

$$C_i = \frac{\phi_{u_i y_i}(w)}{(1 - M_i) \phi_{y_i}(w)} \tag{24}$$

Equation (24) is a nice form, due to the known variables in the right side. Based on this form (24), our proposed direct data driven control is reformulated as the following detailed steps.

Step 1: Collect data $\{u_i(t), y_i(t)\}_{t=1}^{N}$ for each UAV, $i = 1, 2, \cdots M$, and N is the total number of the collected data.

Step 2: According to the control goal, the desired or expected performance is reformulated as one transfer function M_i.

Step 3: Use the collected output to compute the external input $r_i(t) = M_i^{-1} y_i(t)$.

Step 4: Compute the power spectrums $\phi_{u_i y_i}(w)$ and $\phi_{y_i}(w)$.

Step 5: One rough distributed controller is chosen as $C_i = \frac{\phi_{u_i y_i}(w)}{(1-M_i)\phi_{y_i}(w)}$.

Step 6: Check whether $u_i(t) - C_i(1-M_i)r_i(t) = 0$, if it holds then accept that rough distributed controller, or go to step 1 until to be satisfied.

The above six steps are formulated as the following algorithm format for well understanding.

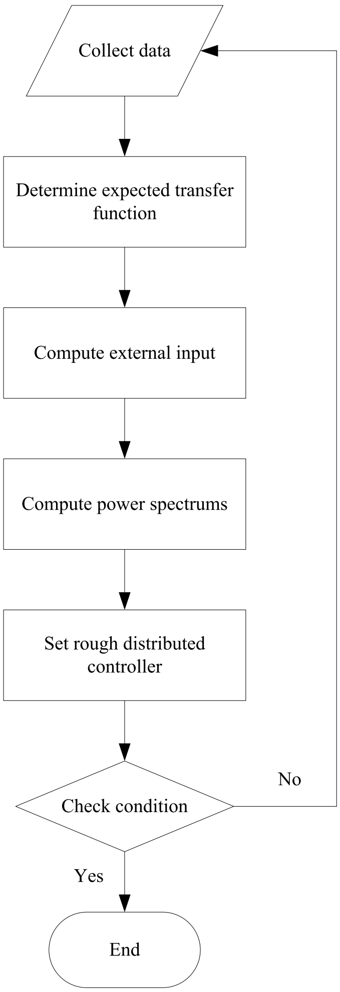

FIGURE 7. Algorithm format.

IV. SIMULATION EXAMPLE

To prove our proposed control architecture and direct data driven control for UAVs formation, here one simulation example about UAVs formation path or trajectory planning is introduced. The cooperative control problem of our multiple UAVs is established when our UAVs can carry out reconnaissance and strike missions in the hostile environment. The goal of designing mission coordination layer is to deal with multiple attack targets at the same time. The objectives of the reconnaissance and strike process include: 1) to navigate our UAV safely in an enemy environment, and to avoid the necessary obstacles and the threat of enemy radar or artillery shells; 2) to realize the location and accurate tracking of the search target; 3) to realize the recognition and detection of the search target; 4) to achieve high precision tracking performance for the detectable target. The simulation architecture analysis framework of this paper is applied to the trajectory planning simulation experiment of UAV in 3D mission environment. The controller design strategy for trajectory planning is contained in the function module of the architecture.

Set the task environment within one square ares, the original position and terminate position are (0,0) and (310,310) respectively. There are five mountains as the terrain threats, where three of them are the radar threats, plotting in Figure 8.

During the whole simulation example, equation (1) is the dynamic equation for each UAV. The optimal distributed controller is yielded through solving that minimization problem (21), and the detailed implementation programs are written

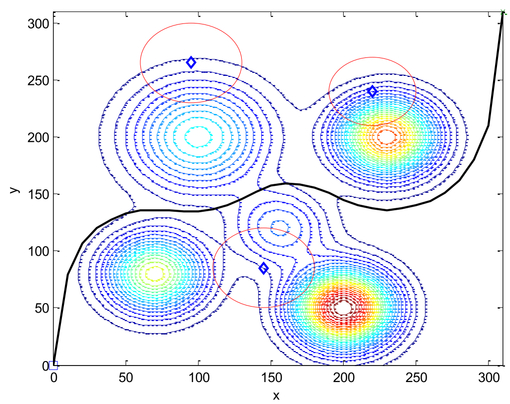

FIGURE 8. The terrain threats.

in the functional module. The lowest physical layer includes some hardware, for example, flight computer, sensors, and human-machine interface etc. Let us apply the matlab program, written for direct data driven control strategy, into the functional module, then it can be adopted automatically. The whole algorithm process is seen in above six steps, which run iteratively until to terminate the zero error. The error function

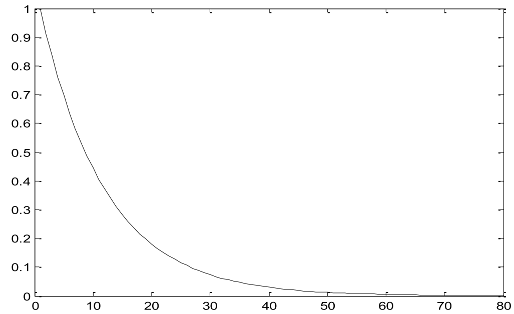

FIGURE 9. Cost function with time.

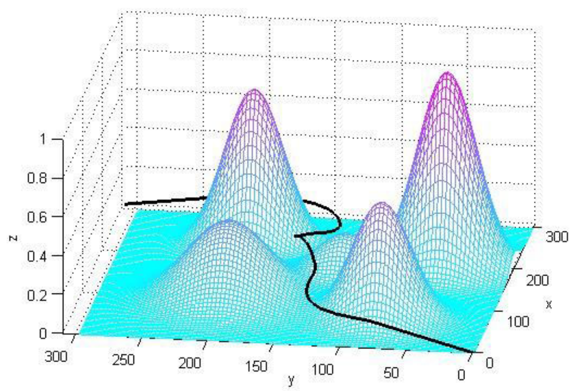

FIGURE 10. UAV trajectory.

in equation (21) is also one quadratic cost function, whose value changes with time increase. Figure 9 shows the curve about that cost function with time. From this curve, the cost function is keeping decreased with time increase.

Figure 10 depicts a three-dimensional track map and contour lines. According to the diagram, the obtained route can effectively avoid the terrain threat and radar threat in the mission area, and the security of UAV can be guaranteed by following the optimal route. The selected tracks of each UAV can avoid the known threat area, and have lower range cost, and the different tracks are relatively scattered in space because of the addition of the clustering algorithm contained in the function module, there was no clustering of multiple candidate tracks.

V. CONCLUSION

To solve the problem of task cooperative planning for UAVs formation, a new cooperative control architecture is proposed to achieve the effective cooperation of UAVs formation. This cooperative control architecture provides a unified structure for various function modules, being used in the task planning. Consider this UAVs formation dynamic network, we consider the distributed controller design problem through our proposed direct data driven control strategy, i.e. each controller is designed from the collected data in detail. As the considered UAVs formation dynamic network corresponds to one complex network structure, there are lots of unseen parts, being unknown to us. So latter we want to use topology theory and graph information to exploit this complex network structure.

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