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NEURAL-NETWORK ADAPTIVE DECENTRALIZED FORMATION CONTROL

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Abstract

In this work, an adaptive decentralized formation control is proposed to cancel the effect of time-varying disturbances that enter the control input. A neural-network adaptive element is added to the input of the collective dynamics, maintaining the original structure of the decentralized formation control. In this way, the formation is controlled linearly, and the adaptive element provides disturbance rejection capabilities.

Keywords: Neural-networks, decentralized formation control, adaptive control.

1. Introduction

In recent years the control of multiple vehicles has regained attention due to numerous new applications, which require to control a large group of drones, satellites, and other flight vehicles for commercial and military applications. Besides, the use of quadcopters has become popular because they are accessible and easy to implement with an aid of commercial products. The way to control this group of vehicles to achieve a common objective is known as Formation Control. To address the formation control problem, many approaches are available such as: leader-follower [1], behaviour-based approach [2], virtual structure method [3] and decentralized formation control [4][5]. Among them, decentralized formation control offers a simplified and easier way to control a group of vehicles than the other approaches. By using graph theory, it is possible to define the connections among vehicles and control the group towards a common goal.

In more realistic applications, a formation is subject to disturbances and uncertainties. In [4] researchers proved necessary conditions for a decentralized linear stabilizing feedback, however, this approach does not consider disturbances. To cope with this problem, robust and adaptive techniques are available. In [6] the decentralized formation flight is controlled using PID technique, the integral action gives robustness to the system to regular perturbations, however when a time-varying disturbance is considered, the performance of the system response is degraded. Furthermore, in [6][7] robust control using sliding mode control is proposed. The main drawback of these nonlinear control approaches is that they increase the complexity of the decentralized control law and make the stability analysis subject to nonlinear control theory.

In this work, a neural-network augmentation of the existing decentralized linear control is proposed based on [8]. This approach offers two advantages: the original structure of the formation control is not modified, and the adaptive element is simply added to the system. Besides, the neural-network adaptive component provides disturbance rejection capabilities.

2. Decentralized Formation Control

We assume a formation of N vehicles with the same dynamics

$$\dot{x}_i = A_v x_i + B_v u_i \qquad i = 1,\dots,N \qquad x_i \in \mathbb{R}^{2n} \tag{2.1}$$

Where x_i represents each vehicle variables for position and velocity of n dimension, and u_i represents the control input. Also, matrices A_v and B_v have the form:

$$A_v = diag\left(\begin{bmatrix} 0 & 1 \\ 0 & a_{22}^{(1)} \end{bmatrix},\dots,\begin{bmatrix} 0 & 1 \\ 0 & a_{22}^{(n)} \end{bmatrix}\right) \qquad B_v = I_n \otimes \begin{bmatrix} 0 \\ 1 \end{bmatrix} \tag{2.2}$$

In the previous equation, the odd entries of x are position variables, and the even entries are the velocity variables represented by vectors x_p and x_v respectively. Thus, the following relation holds:

$$x = x_p \otimes \begin{bmatrix} 1 \\ 0 \end{bmatrix} + x_v \otimes \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

Then let's define the formation vector h

$$h = h_p \otimes \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

Here h_p represent the position of the desired formation.

The formation of N vehicles is said to be in formation if there are some vectors q_p and q_v such that $x_{p_i} - h_{p_i} = q_p,\ x_{v_i} = q_v,\ \forall i = 1,\dots,N$. Then the vehicles converge to a formation h when $x_{p_i}(t) - h_{p_i} - q_p(t) \to 0$ and $x_{v_i}(t) - q_v(t) \to 0$ when $t \to \infty$, $\forall i = 1,\dots,N$. Then the objective is to design a feedback control law that guides the vehicles to a desired formation.

Then, the output vector z can represent the relative information

$$z_i = \sum_{j \in \mathrm{N}_i} \left((x_i - h_i) - (x_j - h_j) \right) \qquad i = 1,\dots,N$$

Taking Eq. (2.1) we can define the collective dynamics:

$$\dot{x} = Ax + Bu \tag{2.3}$$

where $A = I_N \otimes A_v$, $B = I_N \otimes B_v$. With the output vector $z = L(x-h)$, a control law same as in [4] is used:

$$u = FL(x-h) = Fz \tag{2.4}$$

Where $L = L_G \otimes I_{2n}$ and $u = FL(x-h) = Fz$, $F_v = \begin{bmatrix} f_1 & f_2 & 0 & 0 \\ 0 & 0 & f_1 & f_2 \end{bmatrix}$, with L_G as the Laplacian Matrix of a graph G, representing the interactions among a group of vehicles.

We can also write the control input for each vehicle as:

$$u_i = \sum_{j\in N_i} f_1\left(\left(x_{p_i} - h_{pi}\right) - \left(x_{p_j} - h_{p_j}\right)\right) + f_2(x_{v_i} - x_{v_j}) \qquad i = 1,\dots,N \tag{2.5}$$

The closed-loop dynamics can be expressed as follows:

$$\dot{x} = \left(A + BFL\right)x - BFLh$$

It was shown in [1] that having $A_v + \lambda B_v F_v$ Hurwitz will make:

$$z = L(x-h) \to 0$$

Then $H = A_{veh} + \lambda B_{veh} F_{veh} = \begin{bmatrix} 0 & 1 \\ 0 & a_{22} \end{bmatrix} + \lambda \begin{bmatrix} 0 & 1 \\ f_1 & f_2 \end{bmatrix}$ with characteristic equation:

$$p(s) = s^2 - (a_{22} + \lambda f_2)s - \lambda f_1$$

The gains f_1 and f_2 satisfy the following relation

$$a_{22} + \lambda f_2 < 0, \quad \lambda f_1 < 0 \tag{2.6}$$

with λ a nonzero eigenvalue of L_G .

The control gain F , can be designed using any kind of linear controller. For example, by using LQR approach, $(-6db, \infty)$ gain margin and $(-60^\circ, 60^\circ)$ phase margin are guaranteed.

3. Augmented Decentralized Formation Control with Adaptive NN

In this section, a neural network augmentation of existing decentralized control is described as shown in Fig. (1). In this approach, the neural network is simply added to the system, preserving the existing control architecture [8].

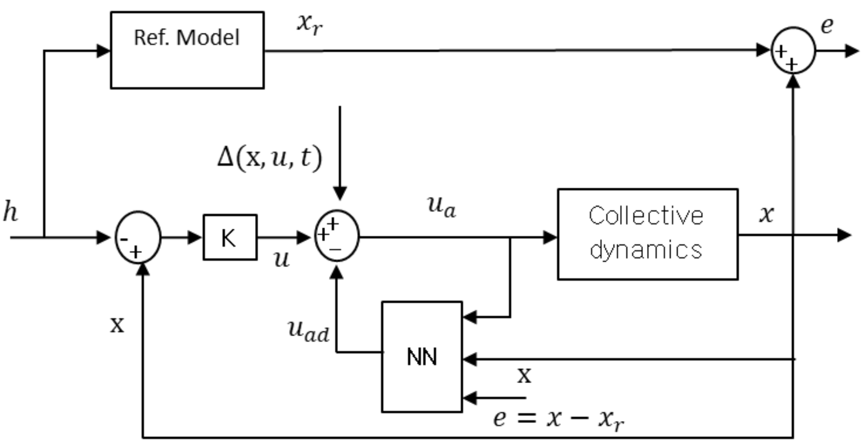

Figure 1 - Augmented adaptive decentralized formation control.

Control augmentation and error equation

Let us recall the collective dynamics from (2.3) with control input (2.4):

$$\dot{x} = Ax + Bu$$
$$u = FL(x - h)$$

which can be seen as an approximation of a nonlinear system of the form:

$$\dot{x}(t) = f(x(t), u(t)) \tag{3.1}$$

If we make $\hat{A} = (A + BFL)$, $\hat{B} = BFL$ and then introduce an uncertainty term $\Delta(x,u,t)$, the closed-loop system becomes:

$$\begin{aligned}\dot{x}(t) &= Ax(t) + B\left[u(t) + \Delta(t,x,u)\right] \\ &= (A + BFL)x(t) - BFLh + B\Delta(t,x,u) \\ &= \hat{A}x(t) - \hat{B}h + B\Delta(t,x,u)\end{aligned} \tag{3.2}$$

Then, we define a reference system:

$$\dot{x}_r(t) = \hat{A}x_r(t) - \hat{B}h \tag{3.3}$$

Using previous expressions and taking $e = x_r - x$, the error dynamics is constructed as:

$$\begin{aligned}\dot{e} = \dot{x}_r - \dot{x} &= \hat{A}(x_r - x) - B\Delta(x,u) \\ &= \hat{A}e - B\Delta(x,u)\end{aligned} \tag{3.4}$$

Now, we define the augmented control input as:

$$u_a(t) = u(t) - u_{ad}(t) \tag{3.5}$$

where u_{ad} is the adaptive signal, which is aimed to cancel the uncertainty term $\Delta(t,x,u)$. It is assumed that $\Delta(t,x,u)$ can be written as a linear combination of some basis functions $\psi(x,u)$

$$\Delta(t,x,u) = W^T\psi(x,u)$$

However, since the adaptive signal provides an approximation of the uncertainty, it is described as:

$$u_{ad}(t) = \hat{\Delta}(t,x,u) = \hat{W}^T\psi(x,u) \tag{3.6}$$

such that the approximation is bounded as $\left|\hat{W}^T\psi(x,u) - W^T(x,u)\psi(x,u)\right| \le \varepsilon_{\max}$

Introducing the augmented control $u_a(t)$ to expression (3.2) gives:

$$\begin{aligned}\dot{x}(t) &= Ax(t) + B\left[u(t) + \Delta(t,x,u) - u_{ad}(t)\right] \\ &= \hat{A}x - \hat{B}h - B\left[\left(\hat{W} - W\right)^T\psi(x,u)\right]\end{aligned} \tag{3.7}$$

Then, the error equation becomes:

$$\begin{aligned}\dot{e} &= \hat{A}e + B\left[\left(\hat{W} - W\right)^T \psi(x,u)\right] \\ &= \hat{A}e + B\left[\Delta W^T \psi(x,u)\right]\end{aligned} \tag{3.8}$$

We define the Lyapunov candidate:

$$V(e,\Delta W) = e^T P e + tr\left(\Delta W^T \Gamma \Delta W\right) > 0 \tag{3.9}$$

Where $P = P^T > 0$ satisfies the Lyapunov equation $\hat{A}^T P + P\hat{A} = -Q$, with $Q = Q^T > 0$.

The time derivative of $V(e,W)$ along (3.8) gives:

$$\dot{V}(e,\Delta W) = -e^T Q e + 2tr\left(\Delta W^T\left[\Gamma^{-1}\dot{\hat{W}} - \psi(x,u)e^T P B\right]\right) \le 0 \tag{3.10}$$

Then $e(t)$ and $W(t)$ are uniformly ultimately bounded (UUB). Furthermore, by Barbalat's lemma It was proven that $e(t)$ is indeed asymptotically stable [9].

Uncertainty restrictions

If then the corrective signal $u_{ad}(t)$ is built such that:

$$u_{ad}(t) = \hat{\Delta}(t, x, u - u_{ad}) \tag{3.11}$$

This expression represents a fixed-point problem, because u_{ad} is a function of itself. Thus, a sufficient condition for the existence to a solution of this problem is required:

$$\left\|\frac{\partial \Delta}{\partial u_{ad}}\right\| < 1 \tag{3.12}$$

Differentiating Eq. (3.1) and Eq. (3.2) will give an expression for $\Delta(\cdot,\cdot)$:

$$\Delta = \left(B^T B\right)^{-1} B^T \left(f(x,u) - Ax - Bu\right) \tag{3.13}$$

The inequality (3.12) is satisfied when

$$\left\|\frac{\partial \Delta}{\partial u_{ad}}\right\| = \left\|B^T\left(\frac{\partial f}{\partial u} - B\right)\right\| < 1 \tag{3.14}$$

Neural Network

The augmented adaptive approach allows us to use any adaptive element to approximate the uncertainty term $\Delta(t,x,u)$. Here, a RBF neural network is used to obtain the corrective signal u_{ad} as in Eq. (3.6), where $\psi(x,u)$ is a radial basis function vector (RBF) [10].

The weight update law is derived from Eq. (3.10) as:

$$\dot{\hat{W}} = -\Gamma e^T PB\psi(x,u) \tag{3.15}$$

Then to keep the adaptive $\hat{W}$ parameter bounded some modifications to adaptation law are required such as e-modification, σ-modification and projection operator.

4. Simulation and Results

In order to test the proposed methodology, we try to control a group of 5 quadcopters. The purpose is that the quadcopters can maintain a desired 'V' position (relative distance) under the presence of an external perturbation (wind). The simulation analysis is performed using Simulink-MATLAB environment.

From Eq. (2.2), it can be seen that the vehicles dynamics are modelled as a double integrator position-velocity model. However, in real world applications quadcopter dynamics are nonlinear by nature. Here we use a 6-DOF quadcopter dynamic model. Applying feedback linearization, we can obtain the required position-velocity model. Thus, a Control Augmentation System (CAS) for position and orientation is applied, using Incremental nonlinear dynamic inversion (INDI). The two-time scale separation principle was utilized to separate the system into the inner (faster) loop for attitude control and the outer (slower) loop related to the translational dynamics. The use of INDI is beneficial because it simplifies the feedback linearization process and provide robustness to unmodeled dynamics.

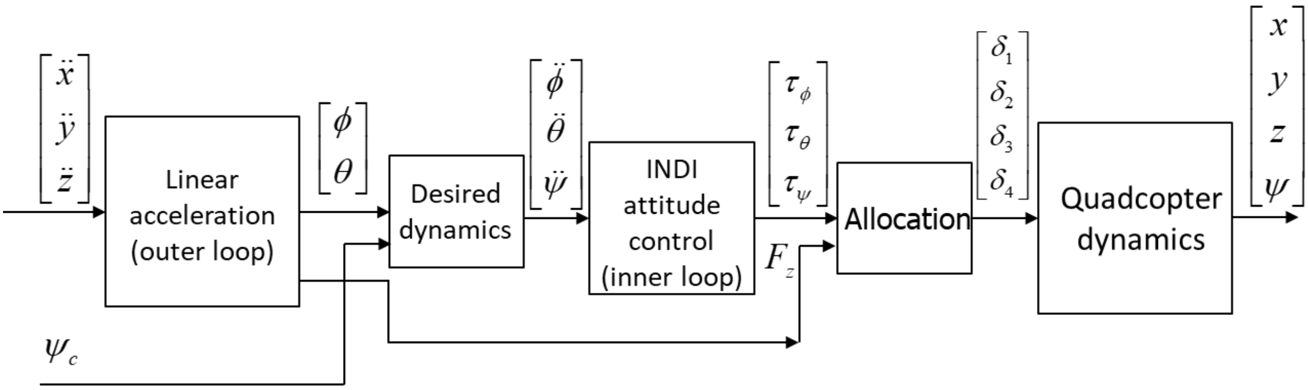

Figure 2 - Block diagram of INDI with two-time scale separation

Fig. (2) shows the block diagram of this approach. Notice that the inputs are not the position commands as in a normal CAS, instead, the acceleration terms are needed. This is because the decentralized formation control will provide the input for the system of each vehicle.

For a formation of 5 vehicles $(N = 5)$, considering dimension $n = 3$, from Eq. (2.1) we have:

$$\dot{x}_i = A_v x_i + B_v u_i \qquad i = 1, \ldots, N \qquad x_i \in \mathbb{R}^{2n}$$

$$\begin{bmatrix} \dot{x} \\ \ddot{x} \\ \dot{y} \\ \ddot{y} \\ \dot{z} \\ \ddot{z} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ \dot{x} \\ y \\ \dot{y} \\ z \\ \dot{z} \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} = A_v x_i + B_v u_i$$

And the collective dynamics is

$$\dot{x} = Ax + Bu$$

Where $x \in \mathbb{R}^{2nN}$ and $u \in \mathbb{R}^{nN}$

Then, the control law $u = FL(x - h)$ is designed with Laplacian matrix L_G for a complete graph of 5 vehicles:

$$L_G = \begin{bmatrix} 4 & -1 & -1 & -1 & -1 \\ -1 & 4 & -1 & -1 & -1 \\ -1 & -1 & 4 & -1 & -1 \\ -1 & -1 & -1 & 4 & -1 \\ -1 & -1 & -1 & -1 & 4 \end{bmatrix}$$

The gain $F = I_{15} \otimes \begin{bmatrix} f_1 & f_2 \end{bmatrix}$ is selected satisfying (2.6)

the formation control with INDI is tested under some wind disturbance. This disturbance can be taken as a sine function of the form $\Delta(t) = 3\sin(3t)$. Here we add $a_{22} < 0$ in Eq. (2.2) to make the vehicles stop in a certain position once they converge to the formation h. The desired formation in z-axis was kept at the same level for all drones, thus we can visualize a 2-d graph in (x,y) axis. The augmented neural network provides the adaptation signal u_{ad} that will cancel the time-varying disturbance $\Delta(t)$ as observed in Fig. (1).

Fig. 3. represents the quadcopters formation that reach the new desired formation without the wind disturbance. Achieving formations means that the vehicles maintain the desired ‘V’ formation. It can be seen from Fig. 4-5 that vehicles 3,4 and 5 converge to the same curve, because they maintain the same position in the x-axis. A Similar situation occurs to vehicles 1,2 and 3 that are aligned in the y-axis. In Fig. 4-5 the curves are parallel to each other, meaning the vehicles keep in formation.

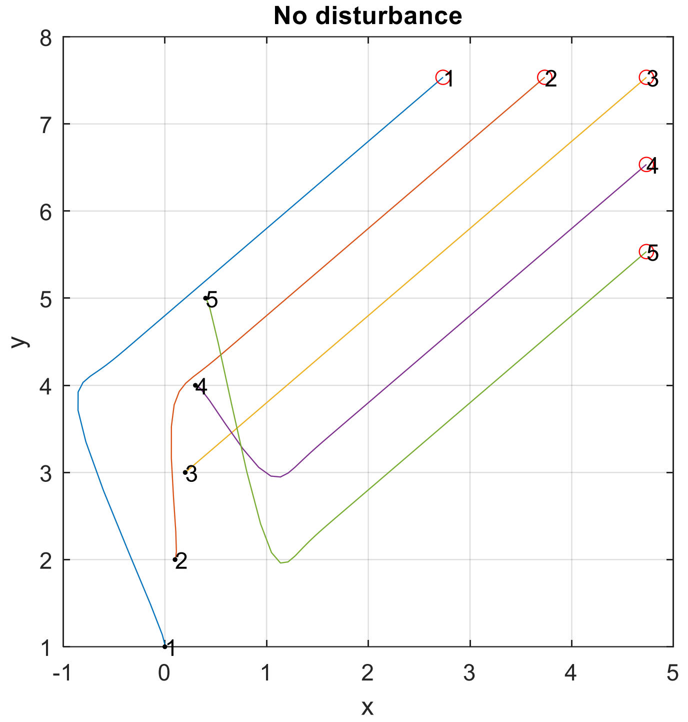

Figure 3 - Formation achieving consensus (no disturbance).

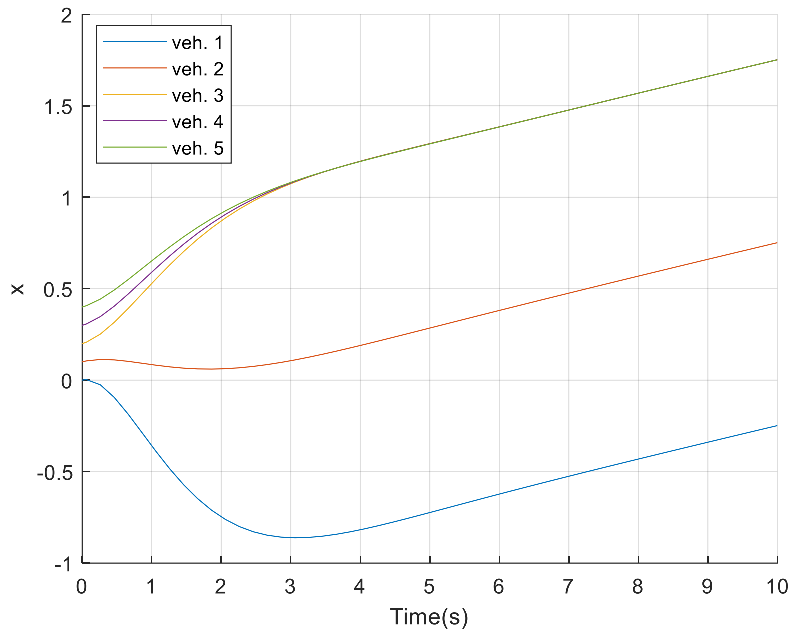

Figure 4 - Vehicle’s position in X-axis.

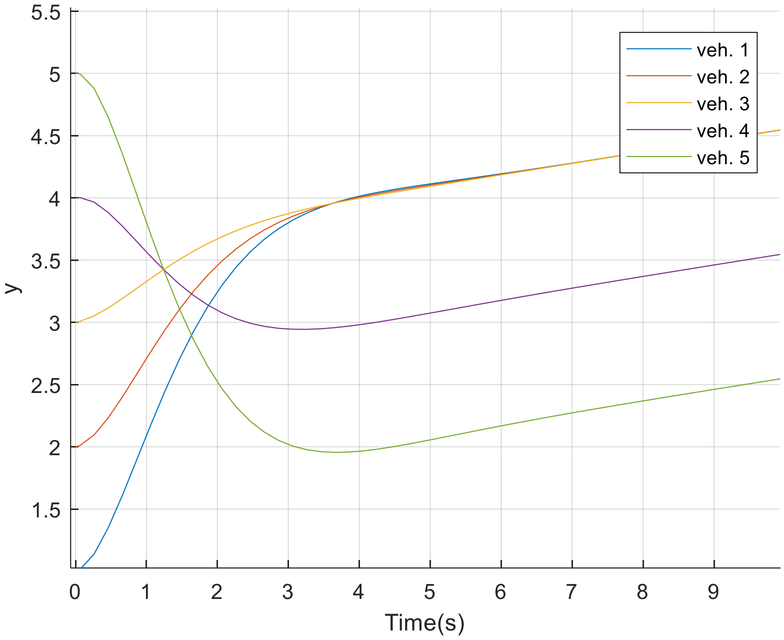

Figure 5 - Vehicle's position in Y-axis.

And, in Fig. 6, we can see that under the disturbance, the decentralized formation control doesn't offer disturbance rejection and thus the quadcopters trajectories are affected. Although the vehicles achieve the formation, they drift in the direction of the wind without stopping. It was expected that they will stop and hover at certain point because $a_{22} < 0$ was chosen.

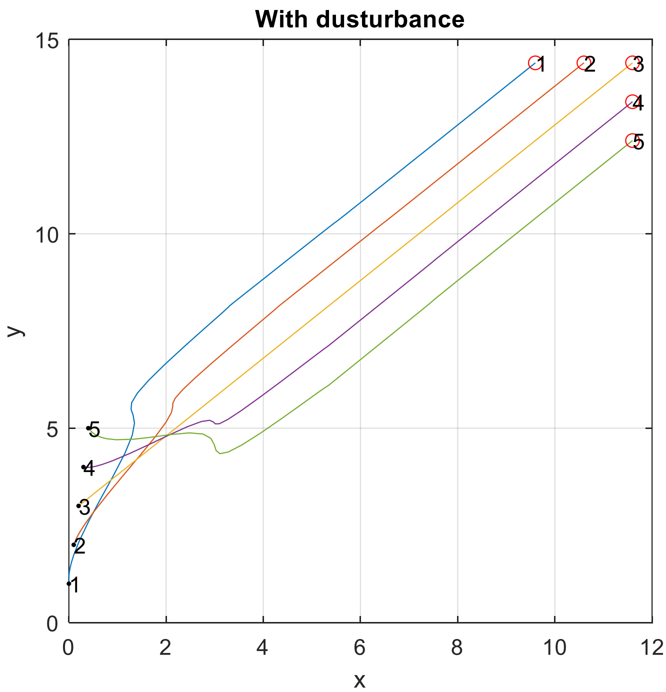

Figure 6 - Formation under wind disturbance without adaptation.

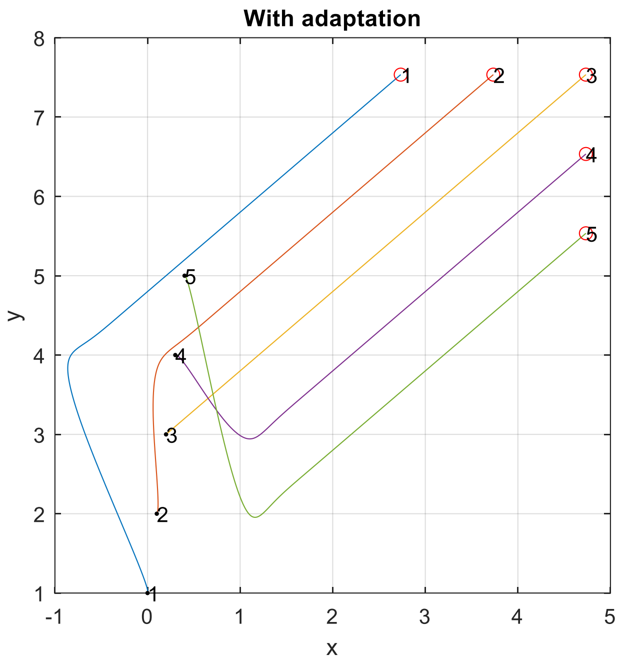

Figure 7 - Formation under wind disturbance with adaptation.

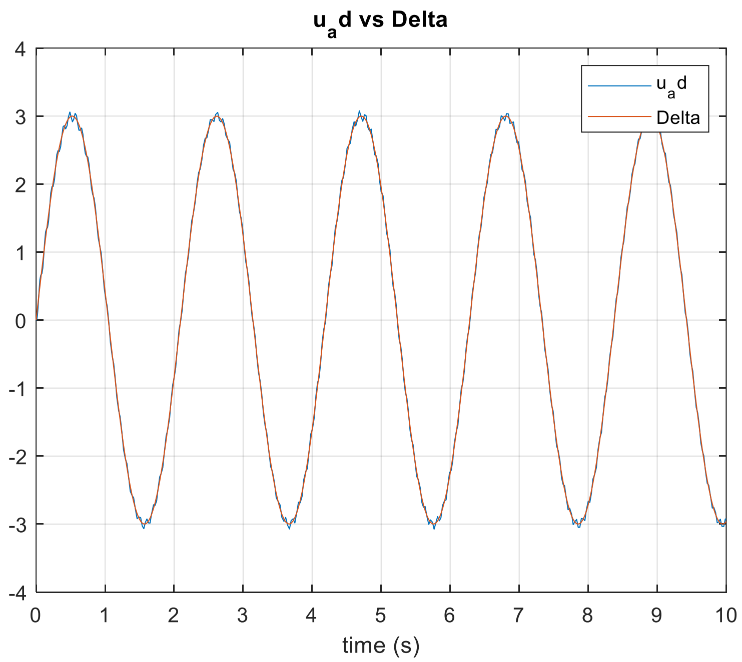

Figure 8 - Adaptation signal vs disturbance.

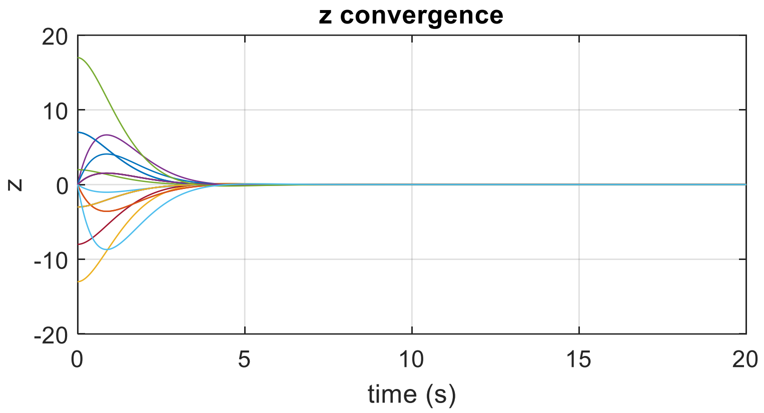

Figure 9 - Convergence of z under wind disturbance with adaptation.

In Fig. 7, the adaptation signal can cancel the uncertainty and the trajectories of the vehicles are not affected. The neural network has the capability to precisely approximate the disturbance term as seen in Fig. 8. Then, the group of quadcopters converge to a desired formation, which means that $z = L(x-h) \to 0$ as $t \to \infty$, as showed in Fig. 9.

5. Conclusions

the use of an augmented adaptive element preserves the control architecture of the formation control. It means the formation is still controlled linearly, having extra disturbance rejection capabilities due to the neural network approximation capabilities.

Additionally, the quadcopter's nonlinear dynamics are converted to a position-velocity model using INDI. This provides a more realistic approach and gives robustness to unmodeled dynamics of each vehicle.

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