A novel data-driven control for fixed-wing UAV path following

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A Novel Data-driven Control for Fixed-Wing UAV Path Following

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***Abstract*—In this paper, a novel data-driven control algorithm is proposed to adaptive control for fixed-wing (Unmanned Aerial Vehicle) UAV path following using input and output (I/O) data. Differently from model based control, data-driven control reduces the dependence of accurate mathematics model in process of controller designation. The key difficulty in fixed-wing UAV path following is that the model of UAV is generally underactuated and nonlinear, and easy to be affected by disturbances. The unique feature of this paper is that we explicitly employ data-driven control to design controller directly in two dimensions at constant height to overcome the drawback of dynamical uncertainties and wind disturbances. The tracking error is guaranteed converging to 0 and simulation results in MATLAB environment show the effectiveness and applicability of the control law.**

I. Introduction

Recently, researches on control of (Unmanned Aerial Vehicle) UAV have attracted great attentions from a great deal of research communities [1][2]. Many controllers have been successfully developed in various kinds fields [3], which include formation control[4], auto landing[5], and path-following[6]. Among them, path following has been deeply investigated in the literature and a basic requirement is that they must be accurate and robust to wind disturbances [7]. For small and low-cost UAV, it is meaningful to consider the UAV to autonomously follow a predefied path. It can be seen in many practical applications such as take a picture, surveillance, investigation, monitor/report wildfire in forests or traffic in urban [8]. To extend the usefulness of UAV beyond their current applications, the capability of path following accurate is of great significant.

It is well known that reason of limiting achievable tracking precision is input coupling, wind disturbances, dynamical uncertainty, nonlinear model and performance of sensing and control [9]. Because of those factors, finding true accurate and robust control algorithm in fixed-wing UAV path following is difficult. Meanwhile, designing a controller to deal with such a complex system is not a simple process, and classic linear approaches omit some dynamical characters necessarily and do not lead to satisfactory performances [10]. In early methods, various assumptions or simplifications on the UAV dynamics were used to obtain near-accurate solutions.

A method for UAV path following, based on the concept of vector fields (VF), has been introduced in [11], and Lyapunov stability criteria are used. it has been shown that the vector field approach provides asymptotic following for straight-line and circular paths in the presence of constant wind disturbances. A solution to the trajectory-tracking and path-following problem for underactuated autonomous vehicles in the presence of possibly large modeling parametric uncertainty was proposed in [12]. The control strategy is combined with a nonlinear Lyapunov-based tracking technique to obtain a hybrid controller, which is robustness to parametric modeling uncertainty. The problem of path following using a quadrotor equipped with a fully embedded imaging and control system was addressed in [13]. A switching between the measurements coming from imaging and inertial sensors was used to estimate the vehicle parameters required in both regions of operation, and stability of the vehicle was guaranteed via a switching control strategy. A dynamic robust path-following AUV (autonomous underwater vehicle) control has been developed in [14]. The proposed method uses a hybrid robust scheme, relying on classic adaptation scheme design of those dynamic parameters that appear with an affine form, and on switching control for the others. In [7], a detailed analysis of five path-following algorithms was performed with different parameter settings and wind disturbances. The simulation results show that VF path-following technique and NLGL (nonlinear guidance law) algorithm are more accurately than other strategies. Arogeti proposed a controller, which utilized a new transformation that, for the pure rolling case, transfers the model to a chain form [15]. The transformation avoid model singularity and the convergence rate is proportional to the vehicle speed and independent of the vehicle heading.

The common characters of those methods are that kinematical models or dynamical model, are widely used for the control system. However, the uncertainties of model and parameters were rarely considered. Data-driven control (DDC), using I/O data to design controller online or offline, is more simple and independent on priori information of model. There are more than 10 kinds of DDC methods, and model-free adaptive control (MFAC) is proposed for general nonlinear systems. In [16], the estimation of pseudo partial derivative (PPD) is obtained by gradient descent (GD) algorithm. While, without any priori acknowledge, it is difficulty to settle initial value of parameters and there is little guidance for adjustment of parameters, which is easy lead to local minimum or oscillations in earlier stages even result in fail under some circumstances.

Inspired by [19], we employ radial basis function (RBF) neural network to estimate PPD. It is practical and valid that iterative estimation of PPD and resetting algorithm will be omitted.

Contrary to other mentioned approaches, the method proposed in this paper does not require acknowledges of system model or analysis of dynamical rule of UAV. The most contributions of this paper are:

1) A novel data-driven control algorithm is proposed to adaptive control for fixed-wing UAV path following without employing any acknowledges of model of UAV;
2) The PPD is estimated by RBF neural network, which is necessary for estimation of PPD when the control scheme is hybrid.
3) The stability of proposed controller is presented with discrete Lyapunov technique.

Consequently, the proposed controller is simple and easy for implementation. There is no requirement for cost and extremely time consuming process of system identification, and the bounds of uncertain disturbances are assumed unknown. The proposed algorithm, although easy for implementation, still shows significant performance improvement when random disturbances are not negligible.

This paper is organized as follows. the primary introduction of MFAC method and some necessary assumptions and notations are given in Section II. Data-driven path-following control laws are developed in 2-D at constant height in section III. The performance of the control system proposed is illustrated in simulation in Section IV. Section V concludes this paper.

II. Introduction

A. Background and Problem Statement

In the most general path following problems, the objective of developed method is to accurately follow a a predefined path. For a small fixed-wing UAV, only high-level navigation control is considered here and low-level attitude control is achieved via an autopilot system.

The UAV dynamics with low-level control in a 2-D horizontal plane is[13]

$$\begin{aligned} \dot{x} &= V cos(\psi) \\ \dot{y} &= V sin(\psi) \\ \dot{\psi} &= u \end{aligned} \tag{1}$$

where, $(x, y) \in \mathbf{R}^2$ denote the position of a UAV, V is the velocity of UAV in the forward direction, ψ is the yaw of UAV. The definitions of those variables shown in Fig.1.

The main objective of proposed controller is existing a optimal control input $u(k)$, which make the following achieved.

$$\begin{aligned} |\delta(k) - \delta_d| &< \varepsilon \\ u_{min} < u(k) &< u_{max} \end{aligned} \tag{2}$$

where, $\delta(k) = \sqrt{(x(k) - x_d(k))^2 + (y(k) - y_d(k))^2}$ is distance between the UAV position and desired position, $(x_d(k), y_d(k))$ is desired position in time k. δ_d is desired value of distance, ε is endurable bound of error, u_{min} and u_{max} are the minimum and maximum of control input, and these are considered as constraints in proposed controller.

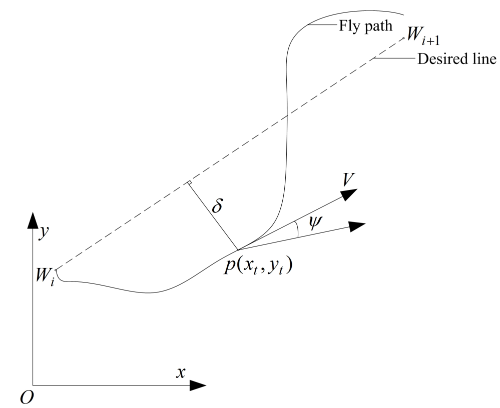

Fig. 1. Coordinate system definitions of the UAV in flight

The key challenge to achieve these objectives is the existing unmodeled dynamics and alterable structure of UAV. In addition, wind disturbances and noises will increase the difficulty of accurate control.

B. Preliminary of MFAC

Consider a class of discrete SISO system

$$y(k+1) = f(y(k), \ldots, y(k-n_y), u(k), \ldots, u(k-n_u)) \tag{3}$$

where, $y(k) \in \mathbf{R}, u(k) \in \mathbf{R}$ are the output and input of system at time k, respectively. n_y and n_u are unknown positive constants. $f(\cdot)$ is a general nonlinear function.

Assumption 1: The system (3) is observable and controllable.

Assumption 2: Omit some finite time point, the partial derivative of $f(\cdot)$ with respect to control input $u(k)$ is continuous.

Assumption 3: Omit some finite time point, system (3) is generalized Lipschitz, that is

$$|\Delta y(k+1)| \leq L|\Delta u(k)|, for \Delta u(k) \neq 0 \tag{4}$$

where L is a constant, $\Delta y(k+1) = y(k+1) - y(k)$ and $\Delta u(k) = u(k) - u(k-1)$ are change of output and input, respectively.

Remark 1: Assumption 1 is common for many reality systems. Assumption 2 is a typical restrained condition for general nonlinear system. Assumption 3 can be treated as some limitation to the rate of the change of control energy. These assumptions are reasonable and acceptable.

Under assumption 1-3, existing a $\phi(k)$, called PPD, then

$$\Delta y(k+1) = \phi(k)\Delta u(k), for \Delta u(k) \neq 0 \tag{5}$$

where $|\phi(k)| \leq L$ is satisfied for all time.

System (5) is an equivalent dynamic linearization presentation of controlled system, and it is distinctly different to model linearization method.

Consider control cost function [16]

$$J(u(k)) = |y^*(k+1) - y(k+1)|^2 + \lambda|u(k) - u(k-1)|^2 \tag{6}$$

where $\lambda > 0$ is a weight factor. $y^*(k+1)$ is desired output.

Substituting (5) into (6), differentiating (6) with respect to $u(k)$ and make it equal to 0.

$$u(k) = u(k-1) + \frac{\rho\phi(k)}{\lambda + |\phi(k)|^2}(y^*(k+1) - y(k)) \tag{7}$$

where $\rho \in (0,1]$ is a step factor.

PPD $\phi(k)$ is, obviously, a time-varying parameter even though the controlled system is a time-invariant system. For estimating PPD, a cost function is also proposed in [16]

$$\begin{array}{c} J(\phi(k)) = |y(k) - y(k-1) - \phi(k)\Delta u(k-1)|^2 \\ \mu|\phi(k) - \hat{\phi}(k-1)|^2 \end{array} \tag{8}$$

solve (8) for maximum or minimum with respect to $\phi(k)$

$$\begin{array}{c} \hat{\phi}(k) = \hat{\phi}(k-1) + \frac{\eta\Delta u(k-1)}{\mu + |\Delta u(k-1)|^2} \\ (\Delta y(k) - \hat{\phi}(k-1)\Delta u(k-1)) \end{array} \tag{9}$$

where, $\lambda > 0$ is a punishment factor, $\eta \in (0,1]$ is a step factor.

III. Controller Design

In this section, the data-driven control strategies for fixed-wing UAV path following in 2-D and 3-D are obtained. For system (2), control input is $u(k)$ and $\delta(k)$ is output. Assume desired output is $\delta^*(k)$, the error of output is defined as

$$e_1(k) = \delta^*(k) - \delta(k) \tag{10}$$

Lemma 1[16]: For the system (2) using the MFAC algorithm (7) and (9), the expectation of PPD estimated value $E(\hat{\phi}(k))$ is bound.

From Lemma 1, proper constants b_1 and b_2 can be defined as

$$0 < b_1 < \hat{\phi}(k) < b_2 \tag{11}$$

The height of fixed-wing UAV is assumed to be constant in problem of path following in 2-D plane. Using the discrete error dynamics are obtained in [17]

$$\begin{array}{c} \delta(k+1) = \delta(k) + \Delta T V sin(\tilde{\psi}(k)) \\ \tilde{\psi}(k+1) = \tilde{\psi}(k) + \Delta T u(k) \end{array} \tag{12}$$

where, ΔT is sample time.

The system (13) can be considered into two subsystem: δ-subsystem and ψ-subsystem.

For δ-subsystem, $\tilde{\psi}(k)$ and $\delta(k)$ can be treated as input and output of system, respectively. Refer to (5), this data model can be presented as

$$\Delta\delta(k+1) = \phi_1(k)\Delta\tilde{\psi}(k) \tag{13}$$

where, $\Delta\delta(k+1) = \delta(k+1) - \delta(k)$, $\Delta\tilde{\psi}(k) = \tilde{\psi}(k) - \tilde{\psi}(k-1)$, $\phi_1(k)$ is PPD of system.

Assume existing a proper input $\tilde{\psi}_d(k)$, which make $\delta(k)$ asymptotically converge to $\delta_d(k)$. Consider the cost function as following

$$J(\tilde{\psi}_d(k)) = |\delta_d(k+1) - \delta(k+1)|^2 + \lambda_1|\tilde{\psi}_d(k) - \tilde{\psi}_d(k-1)|^2 \tag{14}$$

From (7), we can obtain

$$\tilde{\psi}_d(k) = \tilde{\psi}_d(k-1) + \frac{\rho_1\phi_1(k)}{\lambda_1 + |\phi_1(k)|^2}(\delta_d(k+1) - \delta(k)) \tag{15}$$

where $\rho_1 \in (0,1]$ is a step factor.

Cost function of estimation of PPD can be selected

$$\begin{array}{c} J(\phi_1(k)) = |\delta(k) - \delta(k-1) - \phi_1(k)\Delta\tilde{\psi}_d(k-1)|^2 \\ \mu_1|\phi_1(k) - \hat{\phi}_1(k-1)|^2 \end{array} \tag{16}$$

From (9), it is also obtained

$$\begin{array}{c} \hat{\phi}_1(k) = \hat{\phi}_1(k-1) + \frac{\eta_1\Delta\tilde{\psi}_d(k-1)}{\mu_1 + |\Delta\tilde{\psi}_d(k-1)|^2} \\ (\Delta\delta(k) - \hat{\phi}_1(k-1)\Delta\tilde{\psi}_d(k-1)) \end{array} \tag{17}$$

the reset condition is same to *Remark 2*.

For ψ-subsystem, $\tilde{\psi}(k)$ and $u(k)$ can be treated as output and input of system, respectively. The control input $u(k)$ and estimation of PPD $\phi_2(k)$ can be obtained using the same approach in δ-subsystem.

$$\begin{array}{c} u(k) = u(k-1) + \frac{\rho_2\phi_2(k)}{\lambda_2 + |\phi_2(k)|^2} \\ (\tilde{\psi}_d(k-1) + \frac{\rho_1\phi_1(k)}{\lambda_1 + |\phi_1(k)|^2}(\delta_d(k+1) - \delta(k)) - \tilde{\psi}(k)) \end{array} \tag{18}$$

$$\begin{array}{c} \hat{\phi}_2(k) = \hat{\phi}_2(k-1) + \frac{\eta_2\Delta u(k-1)}{\mu_2 + |\Delta u(k-1)|^2} \\ (\tilde{\psi}_d(k) - \hat{\phi}_2(k-1)\Delta u(k-1)) \end{array} \tag{19}$$

So that, a date-driven control strategy has been extended to fixed-wing UAV path following problem in 2-D only using the I/O data.

Remark 3: The control method (19) is directly obtained via I/O data of UAV. The process of controller designation is independent to any acknowledge of (13). Furthermore, (19) can be updated using each group of data step by step.

Remark 4: Although the process of proposed method is divided into two subsystems, the control input (19) is obtained directly. So there is no problem in time accordance and control rate of different subsystem.

IV. Simulation

In this section, two examples are used to verify our control algorithm (19) proposed in former section.

A nonlinear system is employed for collecting I/O data and without additive to control strategy.

$$\begin{array}{c} \dot{x} = V cos(\psi) \\ \dot{y} = V sin(\psi) \\ \dot{\psi} = u \end{array} \tag{20}$$

The desired path is from (0,0) to (300,300) in xy plane. The initial position of the UAV is (0,0) and initial value of heading angle is 0. The value of parameters in control strategy (15) and update law (10) is given $\eta_1 = \eta_2 = 0.2$, $\mu_1 = \mu_2 = 1$, $\rho_1 = \rho_2 = 0.6$, $\lambda_1 = 0.1$, $\lambda_2 = 1$, $\phi_1(1) = \phi_2(1) = 1$, $V = 10$, $\varepsilon = 10^-5$, sampling time $T = 0.01s$.

In Fig. 3, results of data-driven control method is shown. The path of the UAV, represented by a blue solid line, converged to the desired line, donated by a black dot line. Tracking error and heading angle of the UAV are shown in

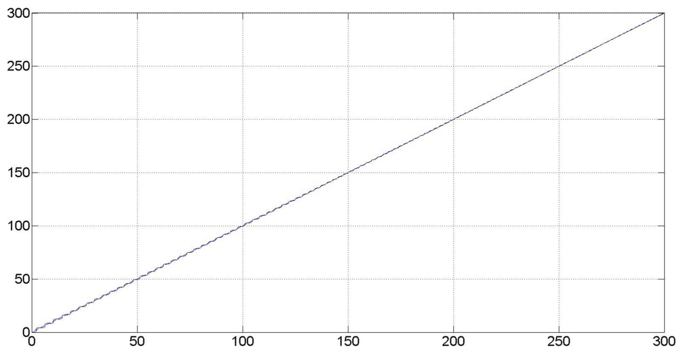

Fig. 2. The path of the UAV

Fig.4 and Fig.5, respectively. The tracking error and heading angle converge to about 0 and $\pi/4$ with some oscillations due to UAV cross the desired path. Although it is slow to converge to the desired path, the tracking error is under 1 from beginning to end.

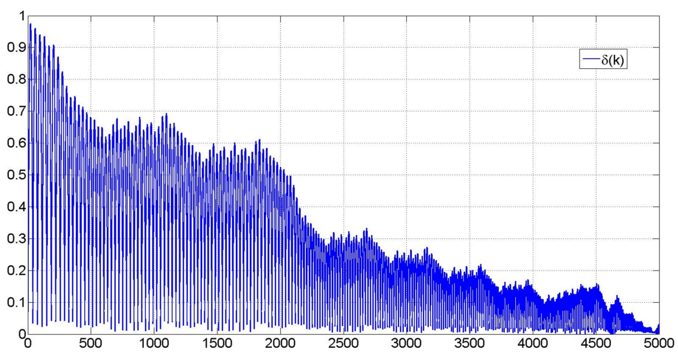

Fig. 3. Tracking error of the UAV

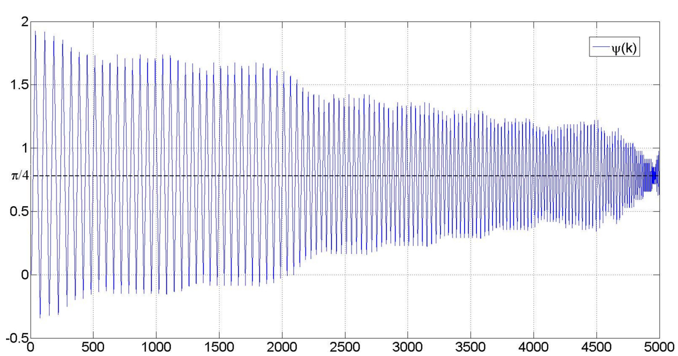

Fig. 4. Heading angle of the UAV

V. Conclusion

In this paper, a novel data-driven control is used as a navigation controller of a small fixed-wing UAV. By employing online I/O data of UAV, the control strategy is proposed directly so that the path of UAV converge to desired path in the end. Although there are some oscillations in the beginning, the tracking error is small and converge to about 0.

However, since the priori acknowledge of UAV is omitted, the initial value of this method is cautious to set. Meanwhile, the results rarely supply guidance to adjustment of parameters. It is needed to considered those problems in the future work. A alternative scheme is that combining data-driven control and model based control. For some loops, data-driven control is utilized to settle unmodeled parts or uncertain parameters; for some loops, model based control is utilized to drive the system efficiently and rapidly.

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