

# Autonomous Takeoff for Unmanned Seaplanes via Fuzzy Identification and Generalized Predictive Control

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**Abstract**—Autonomous takeoff and landing on water, unattended long-term operation capability are the typical characteristics of unmanned seaplanes. As the hydrodynamic forces estimation for unmanned seaplanes is very complicated and sea states are severe, the researches on the modeling, dynamic analysis and controller design are still a great challenge. In this paper, based on the nonlinear mathematical model of the unmanned seaplane, a design methodology via fuzzy identification and generalized predictive control (GPC) is proposed, aiming to improve the sea-keeping ability and avoid the unstable phenomenon in high sea states. A discrete-time model using T-S fuzzy identification is constructed according to the dynamic characteristics in different motion stages, and then GPC algorithm with wave forecasting is applied to achieve autonomous takeoff for the unmanned seaplane. The simulation results show that the proposed approach is capable of making the unmanned seaplane take off successfully with satisfactory performances in three different wave conditions.

## I. INTRODUCTION

**I**N the last decade, with the development of unmanned aerial systems, unmanned seaplanes have appeared as a new vehicle, such as Sea Scout [1], Gull [2] and Flying Fish [3]. As unmanned seaplanes can achieve autonomous takeoff and landing on water without inherent direction constraints of a narrow runway, they are widely applied for a broad range of surveillance and inspection, seaborne medical assistance, environment monitoring and so on. But there exist some inevitable problems during takeoff of unmanned seaplanes. Firstly, longitudinal dynamic instability phenomenon easily occurs when unmanned seaplanes slide along water surface at high speeds, such as porpoising, characterized by an unstable coupling between heave and pitch degrees of freedom [4]. Secondly, it is still an intractable problem to deal with the challenge of hydrodynamic interactions with water surface and unpredictable random waves in high sea states. Therefore, it's necessary to design high-performance controllers to improve the unmanned seaplanes sea-keeping ability, which refers to safety margins in common wave conditions and survivability in extreme waves.

This work was partly supported by the National Natural Science Foundation of China (No. 61273336, 61203003, 61273149), the Special Project for Innovation Methods of MOST (No. 2012IM010200), and CAS Innovation Project (No. YYYJ-1122).

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There is no systematic and comprehensive public literature on controller designing methods for unmanned seaplanes except limited studies. The Flying Fish adopted traditional decoupled proportional-derivative control laws with a mode-based gain scheduling scheme without considering the effects of sea waves [5]. Recently, a longitudinal mathematical model has been developed for unmanned seaplanes [6]. But with the model characterized by high nonlinearities, strong coupling and fast time varying, it is still a challenging problem to design efficient controllers compatible with a wide range of sea conditions. Controllers on unmanned seaplanes should be able to: (1) enhance vertical-plane stability to avoid porpoising; (2) predict the influences from random waves and reduce the water impacts; (3) keep unmanned seaplanes safe and improve the sea-keeping ability in severe sea states.

Since the generalized predictive control (GPC) was proposed by Clarke et al [7], it has been one of the most popular and powerful model-based control methods for a wide class of nonlinear systems. GPC not only receives widespread acceptance in academia [8] [9], but also gains a wide range of applications in industrial process [10]-[12], flight control fields [13] [14], ocean vehicles [15] and so on. Generally, there are two fundamental steps involved in GPC implementation: (1) identification of the system; (2) use of the identified model to design a controller. In this paper, a controller based on T-S fuzzy identification and GPC algorithm is presented so as to achieve autonomous takeoff for the unmanned seaplane. T-S fuzzy identification has been proven suitable to model a large class of complex nonlinear systems, because it can accurately approximate systems by using measured data along with a prior knowledge [16] [17]. In order to utilize the real time information of waves and predict the wave influences for a certain time, GPC algorithm with wave forecasting is proposed to enhance the unmanned seaplane anti-waves capability. This method is demonstrated to have satisfactory control performance by simulation in different sea conditions.

The remainder of the paper is organized as follows: In section 2, the nonlinear mathematical model of the unmanned seaplane is given and the dynamic characteristics are analyzed. In section 3, a controller based on T-S fuzzy identification and GPC is designed to achieve autonomous takeoff for the unmanned seaplane. Furthermore, wave forecasting is added to the GPC algorithm to improve the anti-waves capability. Section 4 shows the performances of the controller in three different wave conditions. Finally, the concluding remarks are summarized in section 5.

## II. NONLINEAR MODEL AND DYNAMIC CHARACTERISTICS ANALYSIS OF THE UNMANNED SEAPLANE

Combining fundamental physical laws and empirical method, the longitudinal mathematical model is derived by [6] for the unmanned seaplane. This model is used for system analysis and controller design using model-based methodologies in this paper.

### A. Coordinates Definition and Longitudinal Mathematical Model

Three right-handed coordinate systems are defined in Fig. 1 for the unmanned seaplane: Earth-fixed coordinate system with  $X_e, Y_e, Z_e$  axes, Body-fixed coordinate system with  $X_b, Y_b, Z_b$  axes and Steady-translating coordinate system with  $X_s, Y_s, Z_s$  axes. These coordinate systems are used to formulate the longitudinal dynamic equations for the unmanned seaplane. In Fig. 1, the variables that represent the angle of attack  $\alpha$ , the angle of pitch  $\theta$  and the velocity  $V$  are also indicated.

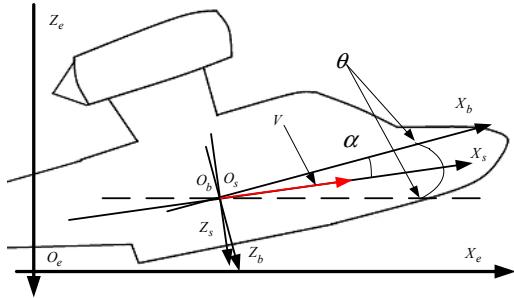


Fig. 1. Coordinate systems of the unmanned seaplane.

The forces acting on the unmanned seaplane can be categorized into weight, hydrodynamic forces, aerodynamic forces and engine thrust as showed in Fig. 2. The nonlinear longitudinal dynamic model of the unmanned seaplane is represented by Eqs(1).

$$\left. \begin{aligned} m\dot{V} &= T \cos(\alpha + \alpha_t) - D_a - N_w \sin \alpha - D_f \cdot \cos \alpha + G_{xa} \\ mV\dot{\alpha} &= mVq - T \sin(\alpha + \alpha_t) - L_a - N_w \cdot \cos \alpha + D_f \cdot \sin \alpha + G_{za} \\ I_y \dot{q} &= M_a + M_w + M_T \\ \dot{\theta} &= q \\ \dot{x}_g &= u \cos \theta + w \sin \theta \\ \dot{z}_g &= -u \sin \theta + w \cos \theta \end{aligned} \right\} \quad (1)$$

where  $T$  is the thrust of engine,  $N_w$  the water pressure normal to the bottom,  $D_f$  the water friction along the bottom,  $L_a$  the aerodynamic lift,  $D_a$  the aerodynamic drag,  $G_{xa}, G_{za}$  the gravity along  $X_s, Z_s$ ,  $M_a, M_w, M_T$  the total pitching moment from air, water and engine,  $x_g, z_g$  the position of the unmanned seaplane along  $X_e, Z_e$ ,  $u, w$  the velocity components of the flying boat along  $X_b, Z_b$ ,  $q$  the pitch angular rate,  $I_y$  the unmanned seaplane's moment of inertia about  $Y_b$ ,  $\alpha_t$  the angle between engine force and  $X_b$ ,  $m$  the mass of the unmanned seaplane.

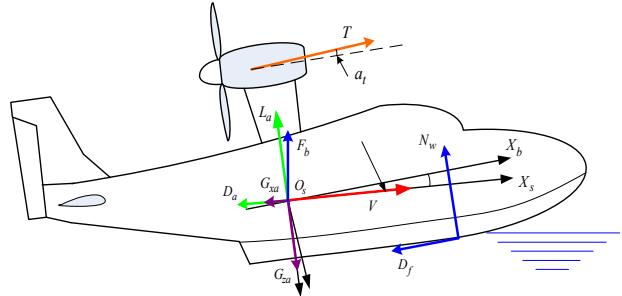


Fig. 2. Forces acting on the unmanned seaplane.

### B. Dynamic Characteristics Analysis of the Unmanned Seaplane

Firstly, dynamic characteristics of the equilibrium states are analyzed. The equilibrium states can be described as maintaining the motion states invariant over a period of time by setting the velocity  $V$  and the elevator deflection  $\delta_e$  to constant values. Fig. 3 shows the trimming values of the height  $h$  which refers to the vertical distance of the center of gravity of the unmanned seaplane from the water surface ( $h = -z_g$ ) for different velocities and elevator inputs. Given  $\delta_e$ , the increase of the height  $h$  as the speed increases suggests stronger hydrodynamic and aerodynamic effect at higher planning speeds. Furthermore, the negative deflection of the elevator has greater influences than positive deflection and it leads to a wider adjustable range of the height in equilibrium running states.

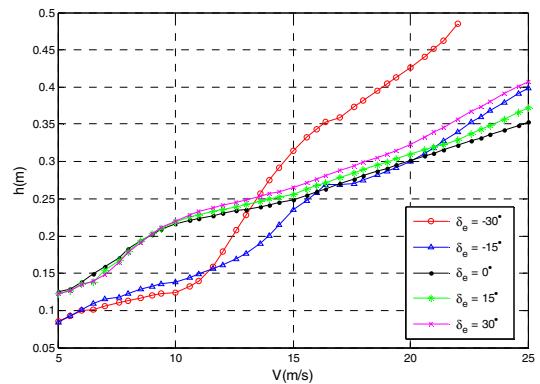


Fig. 3. The trimming values of  $h$ .

Fig. 4 shows the trends of the forces acting on the unmanned seaplane in the case of  $\delta_e = 0^\circ$ . According to the speed and forces situation, it can be divided into four stages during takeoff of the unmanned seaplane: (1) displacing: At lower speed the weight of the body is mainly supported by the static buoyancy forces that are equal to the weight of the displaced fluid. The influences of hydrodynamic lifts and aerodynamic forces can be neglected. (2) semi-planing: The hydrodynamic lifts and aerodynamic forces gradually increase as the speed increases. But compared with the buoyancy forces and hydrodynamic lifts, the aerodynamic forces have a faint effect on the attitude of the unmanned

seaplane. (3) planing: As the unmanned seaplane is lifted out of the water with the increasing speed, the decrease of the wetted length causes the decay of the hydrodynamic lifts. Meanwhile, the aerodynamic forces continue to increase and the buoyancy forces have become very small. (4) takeoff: The hydrodynamic lifts and buoyancy forces gradually decrease to zero and the aerodynamic forces are large enough to guarantee the unmanned seaplane out of the water.

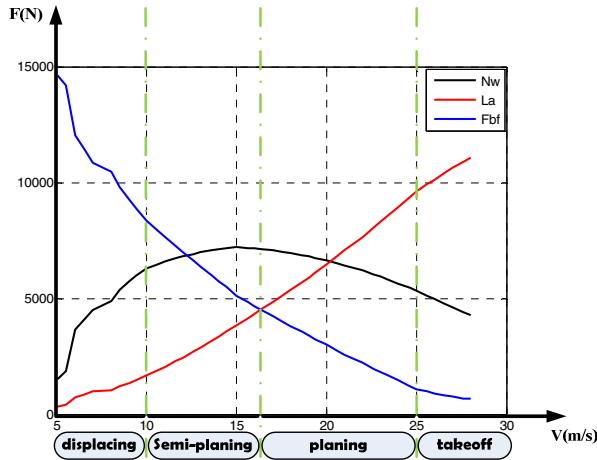


Fig. 4. The trends of the forces acting on the unmanned seaplane.

### III. CONTROLLER DESIGN BASED ON FUZZY IDENTIFICATION AND GPC ALGORITHM

This section aims at developing a GPC controller which can achieve autonomous takeoff for the unmanned seaplane. In order to design the controller effectively, a linear model is obtained through T-S fuzzy identification. AR model based forecasting of sea waves is added to the controller to make the unmanned seaplane adapt to higher sea states.

#### A. T-S Fuzzy Identification of the System

According to the dynamic characteristics of the unmanned seaplane analyzed in the above section, the speed and relative height are picked up as premise variables and a linear controlled auto-regressive integrated moving average model (CARIMA model) is used to represent the local behavior. In order to predict the waves and improve the unmanned seaplane anti-waves capability, the information of waves is added to the model. So the nonlinear model can be described by a T-S fuzzy model defined by the following fuzzy rules:

$$\begin{aligned}
 R_i : & \text{IF } V(t) \text{ is } A_{j(i)} \text{ and } h_w(t) \text{ is } B_{l(i)}, \\
 \text{THEN } & y_i(k) = a_i(z^{-1})y(k-1) + b_i(z^{-1})u(k-1) + c_i(z^{-1})w(k-1) + \xi(k)/\Delta \\
 & a_i(z^{-1}) = a_{i1} + a_{i2}z^{-1} + \dots + a_{in_i}z^{-(n_i-1)}, \\
 & b_i(z^{-1}) = b_{i0} + b_{i1}z^{-1} + \dots + b_{in_i}z^{-n_i}, \\
 & c_i(z^{-1}) = c_{i0} + c_{i1}z^{-1} + \dots + c_{in_i}z^{-n_i}, \\
 & i=1, \dots, L \quad j=1, \dots, m \quad l=1, \dots, n
 \end{aligned} \tag{2}$$

where  $y(k)$  is the model output, the angle of pitch  $\theta$  is selected as the output variable.  $u(k)$  is the model input, the elevator deflection  $\delta_e$  is selected as the input variable.  $w(k)$

is the information of waves, the wave slope angle  $w_v(t)$  is selected.  $R_i$  represents the  $i$  th fuzzy rule,  $L$  is the total number of rules.  $A_{j(i)}, B_{l(i)}$  are the fuzzy sets corresponding to  $V(t), h_w(t)$  in the  $j$  th and  $l$  th fuzzy implication of the  $i$  th fuzzy rule,  $m, n$  are the total number of fuzzy sets  $A_{j(i)}, B_{l(i)}$ .  $h_w(t) = z_g(t) - \zeta(t, x_g, y_g)$ .  $\xi(k)$  is a sequence of white noise.  $\Delta$  is the differencing operator ( $\Delta = 1 - z^{-1}$ ).

Let  $\mu_{j(i)}^A(V(t)), \mu_{l(i)}^B(h_w(t))$  be the membership degree of  $V(t), h_w(t)$  in the fuzzy set  $A_{j(i)}, B_{l(i)}$ , respectively. Then the T-S fuzzy model of the system can be inferred as:

$$y(k) = \sum_{i=1}^L \gamma_i(k) [a_i(z^{-1})y(k-1) + b_i(z^{-1})u(k-1) + c_i(z^{-1})w(k-1)] + \xi(k)/\Delta \tag{3}$$

where

$$\gamma_i(k) = \frac{\bar{\mu}_i(k)}{\sum_{i=1}^L \bar{\mu}_i(k)}, \quad \bar{\mu}_i(k) = \mu_{j(i)}^A(V(t)) \cdot \mu_{l(i)}^B(h_w(t)) \tag{4}$$

The membership functions associated to the fuzzy sets  $A_{j(i)}, B_{l(i)}$  are defined according to the different motion stages of the unmanned seaplane in Fig. 5.  $A_1, A_2, A_3, A_4$  represent the displacing, semi-planing, planning and take-off, respectively. The leaving speed of the unmanned seaplane can be chosen as  $28m/s$ . The sets of the relative height  $B_1, B_2, B_3, B_4$  correspond to  $A_1, A_2, A_3, A_4$ . Z-shaped and S-shaped functions are adopted in both sides of the fuzzy sets and  $\pi$ -shaped functions are adopted in the middle of the fuzzy sets. The parameters of the membership functions are selected according to the trimming values in Fig. 3 and the division of different motion stages in Fig. 4.

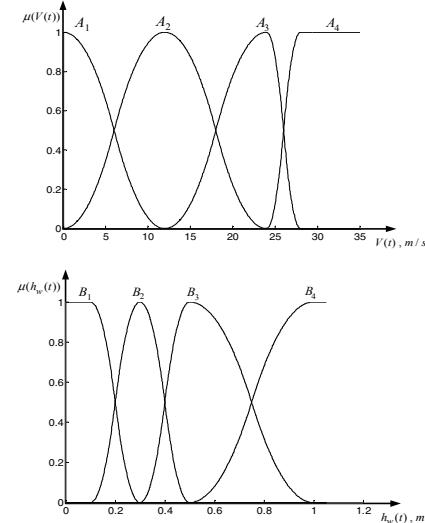


Fig. 5. Definition of the membership functions of the fuzzy sets.

Next, the recursive least square (RLS) method is used to identify the consequence parameters of the model. Thus,  $y(k)$  can be rewritten as:

$$y(k) = \boldsymbol{\varphi}^T(k)\boldsymbol{\theta} + \xi(k)/\Delta \tag{5}$$

where

$$\boldsymbol{\theta} = [\boldsymbol{\theta}_1^T \ \boldsymbol{\theta}_2^T \ \cdots \ \boldsymbol{\theta}_L^T]^T \quad (6)$$

$$\boldsymbol{\varphi}(k) = [\boldsymbol{\varphi}_1^T(k) \ \boldsymbol{\varphi}_2^T(k) \ \cdots \ \boldsymbol{\varphi}_L^T(k)]^T \quad (7)$$

$$\boldsymbol{\theta}_i = [a_{1i} \ \cdots \ a_{n_a i} \ b_{0i} \ \cdots \ b_{n_b i} \ c_{0i} \ \cdots \ c_{n_c i}]^T \quad (8)$$

The least-squares estimate of  $\boldsymbol{\theta}(k)$  satisfies the following recursive equations:

$$\hat{\boldsymbol{\theta}}(k) = \hat{\boldsymbol{\theta}}(k-1) + \mathbf{K}(k)[\Delta y(k) - \boldsymbol{\varphi}^T(k)\hat{\boldsymbol{\theta}}(k-1)] \quad (9)$$

$$\mathbf{K}(k) = \frac{\mathbf{P}(k-1)\boldsymbol{\varphi}(k)}{1 + \boldsymbol{\varphi}^T(k)\mathbf{P}(k-1)\boldsymbol{\varphi}(k)} \quad (10)$$

$$\mathbf{P}(k) = [\mathbf{I} - \mathbf{K}(k)\boldsymbol{\varphi}^T(k)]\mathbf{P}(k-1) \quad (11)$$

The T-S fuzzy model of the system can be easily obtained by the above method.

### B. Derivation and Analysis of GPC Algorithm

To derive the GPC control law, the T-S fuzzy model (3) can be rewritten as:

$$\bar{a}(z^{-1})y(k) = \bar{b}(z^{-1})\Delta u(k-1) + \bar{c}(z^{-1})\Delta w(k-1) + \xi(k) \quad (12)$$

where

$$\bar{a}(z^{-1}) = 1 - \bar{a}_1 z^{-1} - \bar{a}_2 z^{-2} - \cdots - \bar{a}_{n_a+1} z^{-(n_a+1)}, \bar{a}_j = \sum_{i=1}^L \gamma_i(k) a_{ji} z^{-j} \quad (13)$$

$$\bar{b}(z^{-1}) = \bar{b}_1 z^{-1} + \bar{b}_2 z^{-2} + \cdots + \bar{b}_{n_b} z^{-n_b}, \bar{b}_j = \sum_{i=1}^L \gamma_i(k) b_{ji} z^{-j} \quad (14)$$

$$\bar{c}(z^{-1}) = \bar{c}_1 z^{-1} + \bar{c}_2 z^{-2} + \cdots + \bar{c}_{n_c} z^{-n_c}, \bar{c}_j = \sum_{i=1}^L \gamma_i(k) c_{ji} z^{-j} \quad (15)$$

The GPC algorithm is obtained to minimize the following cost function [7]:

$$J(k) = E\left\{\sum_{j=N_1}^{N_2} [y(k+j) - y_r(k+j)]^2 + \sum_{j=1}^{N_u} [\lambda_j \Delta u(k+j-1)]^2\right\} \quad (16)$$

where  $y(k+j)$  is the  $j$ -step ahead output prediction of the system,  $y_r(k+j)$  is the future reference trajectory,  $N_1$  is the minimum costing horizon,  $N_2$  is the maximum costing horizon,  $N_u$  is the control horizon,  $\lambda_j$  is a control weighting sequence.  $N_2 \geq N_u \geq N_1$  is assumed.

Consider the following Diophantine equation:

$$1 = \bar{a}(z^{-1})r_j(z^{-1}) + z^{-j}s_j(z^{-1}) \quad (17)$$

where

$$r_j(z^{-1}) = 1 + r_{j,1} z^{-1} + r_{j,2} z^{-2} + \cdots + r_{j,j-1} z^{-(j-1)} \quad (18)$$

$$s_j(z^{-1}) = s_{j,0} + s_{j,1} z^{-1} + \cdots + s_{j,n_a} z^{-n_a} \quad (19)$$

Multiplying (12) by  $z^j r_j(z^{-1})$  gives the following equality:

$$\bar{a}(z^{-1})r_j(z^{-1})y(k+j) = \bar{b}(z^{-1})r_j(z^{-1})\Delta u(k+j-1) + \quad (20)$$

$$\bar{c}(z^{-1})r_j(z^{-1})\Delta w(k+j-1) + r_j(z^{-1})\xi(k+j)$$

Defining the following equations:

$$\hat{\xi}(k) = r_j(z^{-1})\xi(k+j) \quad (21)$$

$$f_j(z^{-1}) = \bar{b}(z^{-1})r_j(z^{-1}) = f_{j,0} + f_{j,1} z^{-1} + \cdots + f_{j,n_b+j-1} z^{-(n_b+j-1)} \quad (22)$$

$$g_j(z^{-1}) = \bar{c}(z^{-1})r_j(z^{-1}) = g_{j,0} + g_{j,1} z^{-1} + \cdots + g_{j,n_c+j-1} z^{-(n_c+j-1)} \quad (23)$$

Substituting (17), (21)-(23) into (20),

$$y(k+j) = f_j(z^{-1})\Delta u(k+j-1) + g_j(z^{-1})\Delta w(k+j-1) + s_j(z^{-1})y(k) + \hat{\xi}(k) \quad (24)$$

Thus, the best  $j$ -step ahead output prediction of the system can be obtained by

$$y(k+j) = f_j(z^{-1})\Delta u(k+j-1) + g_j(z^{-1})\Delta w(k+j-1) + s_j(z^{-1})y(k) \quad (25)$$

Assuming  $j = N_1, N_1+1, \dots, N_2$ , Eq(25) can be rewritten as the following matrix form:

$$\mathbf{Y}_p(k) = \mathbf{F}_1 \Delta \mathbf{U}_p(k) + \mathbf{F}_2 \Delta \mathbf{U}(k) + \mathbf{G}_1 \Delta \mathbf{W}_p(k) + \mathbf{G}_2 \Delta \mathbf{W}(k) + \mathbf{R} \mathbf{Y}(k) \quad (26)$$

where  $\mathbf{Y}_p(k)$  is the future prediction outputs,  $\mathbf{Y}(k)$  is the current and past system outputs,  $\Delta \mathbf{U}_p(k)$  is the current and future control increment,  $\Delta \mathbf{U}(k)$  is the past control increment,  $\Delta \mathbf{W}_p(k)$  is the current and future wave information,  $\Delta \mathbf{W}(k)$  is the past wave information.  $\mathbf{F}_1, \mathbf{F}_2, \mathbf{G}_1, \mathbf{G}_2, \mathbf{R}$  is corresponding coefficient matrix.

Using Eq(26), Eq(16) can be rewritten as:

$$J(k) = E\{\mathbf{Y}_p(k) - \mathbf{Y}_r(k)\}^T [\mathbf{Y}_p(k) - \mathbf{Y}_r(k)] + \Delta \mathbf{U}_p(k)^T \mathbf{I} \Delta \mathbf{U}_p(k) \quad (27)$$

where  $\mathbf{Y}_r(k)$  is the future reference trajectory outputs,  $\mathbf{I}$  is the control weighting vector.

To minimize  $J(k)$ , the following equation is solved:

$$\frac{\partial J(k)}{\partial \Delta \mathbf{U}_p(k)} = 0 \quad (28)$$

Then the following optimum control increment can be obtained:

$$\Delta \mathbf{U}_p(k) = (\mathbf{F}_1^T \mathbf{F}_1 + \mathbf{I})^{-1} \mathbf{F}_1^T [\mathbf{Y}_r(k) - \mathbf{F}_2 \Delta \mathbf{U}(k) - \mathbf{G}_1 \Delta \mathbf{W}_p(k) - \mathbf{G}_2 \Delta \mathbf{W}(k) - \mathbf{R} \mathbf{Y}(k)] \quad (29)$$

In Eq(29),  $\Delta \mathbf{W}_p(k)$  contains the future wave information and the wave forecasting method will be introduced in next section.

### C. AR Model Based Forecasting of Waves

The above GPC algorithm is capable of utilizing the real time wave information and predicting the wave influences for a certain time. The future wave information is included in the term  $\Delta \mathbf{W}_p(k)$  of the GPC algorithm. Auto-regressive model (AR model) is adopted to describe the trends of wave motion and obtain the states of the waves in the future, which can be expressed as the following form:

$$\begin{aligned} d(z^{-1})w(k) &= \xi(k) \\ d(z^{-1}) &= 1 + d_1 z^{-1} + \cdots + d_{n_w} z^{-n_w} \end{aligned} \quad (30)$$

Eq(30) can be transformed into the least square format:

$$w(k) = \boldsymbol{\psi}^T(k) \boldsymbol{\theta}_w \quad (31)$$

$$\boldsymbol{\psi}(k) = [-w(k-1) \ \cdots \ -w(k-n_w)]^T \quad (32)$$

$$\boldsymbol{\theta}_w = [d_1 \ \cdots \ d_{n_w}]^T \quad (33)$$

The forgetting factor recursive least square algorithm (FFRLS) [18] is adopted to identify the unknown parameter  $\boldsymbol{\theta}_w$ , which can be calculated by

$$\hat{\boldsymbol{\theta}}_w(k) = \hat{\boldsymbol{\theta}}_w(k-1) + \mathbf{K}(k)[w(k) - \boldsymbol{\psi}^T(k)\hat{\boldsymbol{\theta}}_w(k-1)] \quad (34)$$

$$K(k) = \frac{\mathbf{P}(k-1)\boldsymbol{\psi}(k)}{\mu + \boldsymbol{\psi}^T(k)\mathbf{P}(k-1)\boldsymbol{\psi}(k)} \quad (35)$$

$$\mathbf{P}(k) = \frac{1}{\mu} [\mathbf{I} - K(k)\boldsymbol{\psi}^T(k)]\mathbf{P}(k-1) \quad (36)$$

#### D. Reference Signal

In the proposed controller, we choose the angle of pitch  $\theta$  as the control input variable, and it is a key problem to select the desired reference signal that achieves the autonomous takeoff for the unmanned seaplane. According to the dynamic characteristics of the unmanned seaplane in different motion stages, the reference signal can be expressed by the following T-S fuzzy reasoning [19]:

$$\begin{aligned} R_{j,l} : & \text{IF } V(t) \text{ is } A_j \text{ and } h_w(t) \text{ is } B_l, \\ & \text{THEN } \theta_{j,l} = a_j \cdot (b_{j,l} + w_v(t)) + c_j \cdot \theta_{j,l}^c + k_q \cdot q(t) \end{aligned} \quad (37)$$

where the definition of the relevant variables and fuzzy sets is similar to section III.  $\theta_{j,l}$  is the reference signal,  $a_j$  is a parameter to achieve the wave following control for the unmanned seaplane,  $b_{j,l}$  is the expected relative angle between the unmanned seaplane and water surfaces,  $c_j$  is a parameter to keep the attitude of the unmanned seaplane in the air,  $\theta_{j,l}^c$  is the expected angle of pitch,  $k_q$  is a parameter to increase the damp of the pitch moments.

The specific calculation and parameter selection of Eq(37) can be found in [19] and there will not be discussed in detail in this paper.

According to the above discussion, a schematic diagram that presents the structure of the GPC controller with wave forecasting is showed in Fig. 6. The dotted line represents the wave information and the solid line represents the states information of the unmanned seaplane.

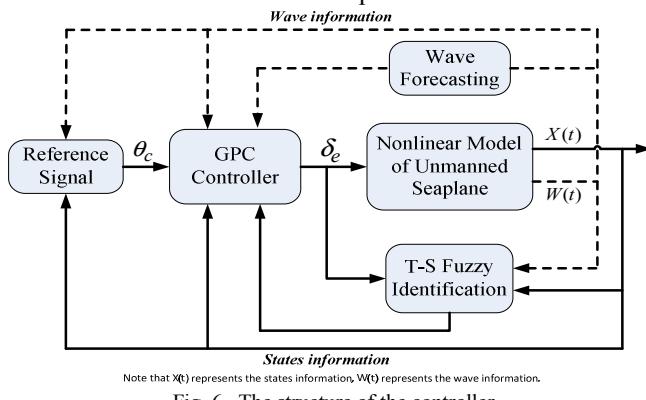


Fig. 6. The structure of the controller.

## IV. SIMULATION RESULTS

In this section, three different wave conditions (calm water, regular wave, irregular wave) are provided to demonstrate the performance of the proposed controller. The initial states of the unmanned seaplane are chosen as  $[V, \alpha, q, \theta, x_g, z_g]^T = [7m/s, 0.121rad, 0rad/s, 0.111rad, 0m, -0.11m]^T$ , while the initial control inputs are  $[\delta_{th}, \delta_e]^T = [1, -0.1122rad]^T$ . The limits of the elevator deflection are  $-30^\circ \leq \delta_e \leq 30^\circ$ . The

orders of the T-S fuzzy model and wave model can be specified by  $n_a = 4$ ,  $n_b = 3$ ,  $n_c = 1$  and  $n_w = 4$ , respectively. The controller parameters are set as follows:  $N_1 = 1$ ,  $N_2 = 100$ ,  $N_u = 5$ ,  $\lambda_j = 1$  ( $j = 1, \dots, N_u$ ).

Firstly, the unmanned seaplane is simulated to achieve autonomous takeoff in calm water. Fig. 7 shows the changes of the states and hydrodynamic lift during takeoff. Fig. 7 (a) (b) suggests that the speed and height increase smoothly until the unmanned seaplane leaves out of water. The deflection of the elevator is given in Fig. 7 (c), which indicates that the actuator saturation only appears in a short time. The hydrodynamic lift is large at lower speed and decreases gradually to zero during takeoff as showed in Fig. 7 (d).

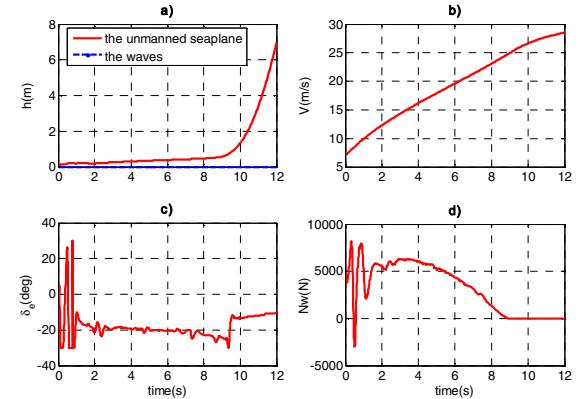


Fig. 7. Performance of the unmanned seaplane in calm water.

Secondly, the simulation is performed in regular wave whose amplitude and wavelength are 0.2m, 50m. The good performances for the height and the speed can be seen in Fig. 8 (a) (b). The unmanned seaplane tracks the waves well until it take off at 9 seconds. The elevator deflection and hydrodynamic lift change in a small range as showed in Fig. 8 (c) (d).

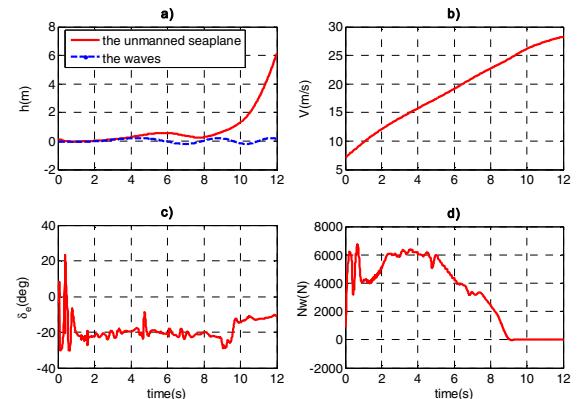


Fig. 8. Performance of the unmanned seaplane in regular wave.

Thirdly, Fig. 9 presents the performance of the controller in irregular wave, which is equivalent to Seastate 3 [20] and the significant wave height is more than one meter. As the distance between the center of gravity and the bottom is only 0.552m for the unmanned seaplane in this paper, this irregular wave belongs to the severe sea state for the unmanned seaplane. There appears the actuator saturation problem several times and the hydrodynamic lift has a large impact on

the unmanned seaplane as showed in Fig. 9 (c) (d). But Fig. 9 (a) suggests that the unmanned seaplane can still follow the wave surfaces very well before it takes off, avoiding being thrown into air and plunged into water. The unmanned seaplane can achieve autonomous takeoff successfully in high sea states via the proposed controller.

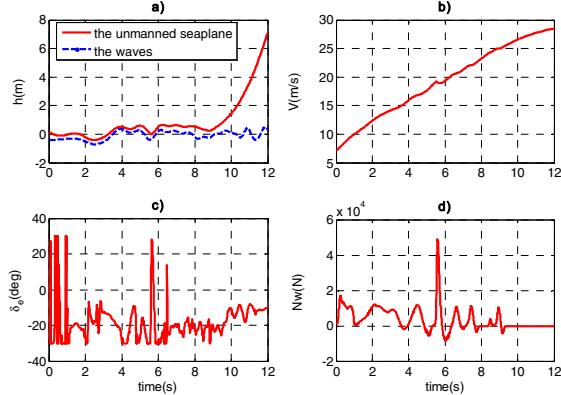


Fig. 9. Performance of the unmanned seaplane in irregular wave.

## V. CONCLUSION

A new control scheme based on fuzzy identification and generalized predictive control is applied to the autonomous takeoff for an unmanned seaplane in this paper. Considering that it is difficult to design the controller using the nonlinear model directly, a linear CARIMA model obtained through T-S fuzzy identification is used to represent the dynamic characteristics of the unmanned seaplane in different motion stages. GPC controller is proposed based on the linear model to achieve the tracking of the desired angle of pitch. As the unmanned seaplane is easily influenced by the unknown wave conditions, the real time information of sea waves must be treated as a key factor in controller design. Wave forecasting is added to the GPC algorithm to improve the anti-waves capability and reduce the wave impacts.

The simulation results show that the proposed control system has satisfactory performances for the unmanned seaplane in different wave conditions, especially in high sea states. The motion stability and sea-keeping ability are improved, which has great significance for the developments and applications of unmanned seaplanes.

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