

Energy Saving Control of Bionic Robotic Fish based on Model-free Adaptive Control[★]

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Abstract: In this paper, an energy-saving model-free adaptive control (MFAC) is proposed for the control of the bionic robotic fish. First, the original MFAC controllers for the speed based on the full form dynamic linearization data model are presented as an example of the controlled variable of the controlled object. Then by modifying the criterion function for control input optimization, an energy-saving MFAC controller is designed to reduce the energy consumption. The proposed method is a data-driven control method, which means that the control system designing process merely needs input and output (I/O) measurement data of the controlled plant, and does not need any model information. Simulation results demonstrate the effectiveness of the improved MFAC in speed and attitude control of the bionic robotic fish.

Keywords: Model-free adaptive control, dynamic linearization data model, bionic robotic fish, energy saving control.

1. INTRODUCTION

To exploit marine resources and realize complex underwater tasks, bionic underwater vehicle has become a hot topic in this field. Due to the characteristics of good fluid property and high swimming efficiency, the flapping wing fish provides better motion performance than the traditional propeller driving model [Wang et al. (2009)]. Lots of excellent work has been done in this field. Among them, batoid fish and its swimming mode attract many researchers' attention. Its swimming requires only a pair of large pectoral fins, so the motion control is main task to tackle with [Lu et al. (2018); Chung et al. (2006)].

Over the years, there are some control methods proposed for the control of the bionic robotic fish, and most of them are designed based on the kinematics model of the designed robotic fish [Li et al. (2010); Niu et al. (2014); Cai et al. (2010)], dynamics model [Shen et al. (2015); Moored et al. (2011a); Moored et al. (2011b)] and central pattern generator control method [Ikeda et al. (2013); Crespi et al. (2008)]. From the system control point of view, they can be recognized as the model based control methods since they are designed by accurate controlled fish mechanic structures or motion dynamics models. However, the performance of these control methods usually significantly depend on the system models, and suffers a lots for their robustness when they are implemented in practical ocean environment.

In order to deal with the strong coupling of underwater motion and nonlinear hydrodynamics [Yoerger and Slotine (1985)], and the questionable performance of the inaccurate fish's modeling based on traditional control methods, a data-driven model free adaptive control method for the bionic robotic fish is proposed in this paper. The data-driven control can provide a new way for the study of bionic robotic fish [Hou et al. (2017); Zhu and Hou (2017)]. As we know, PID control is the first data driven control, and it has gotten numerical successful applications in various fields [Samad (2017)]. However, its control performance to some complex controlled plants usually exhibit a poor behavior due to an improper parameter tunings. Theoretically speaking, a good PID parameter tuning for a complex controlled plant is an impossible task, which is already demonstrated and verified in the past century's control engineering practices due to the fact that the PID controller parameters should be a time-varying ones essentially [Hou and Xiong (2019)]. In this paper, we will use a novel data driven control method, called model-free adaptive control (MFAC), including the PID as a special case, to control the speed and the attitude of the bionic robotic fish.

MFAC, as a data-driven control method for a class of the discrete-time nonlinear systems, was originally proposed by Hou in 1994 [Hou (1994)]. MFAC could be designed merely using the closed-loop input-output data of the controlled plant, and the controller structure is determined by the optimization on the one-step-ahead control input criterion via the dynamic linearization data model, which is dynamically modeled at each working point by using the I/O data with help of the novel concept called pseudo-

[★] This work is supported by National Natural Science Foundation of China (NSFC) under Grants 61833001.

gradient(PG) or pseudo-partial derivative (PPD) of the controlled plant [Hou and Jin (2011b)]. The dynamic linearization technique includes three kind of dynamic linearization data models, that is, the compact-form dynamic linearization (CFDL) data model, the partial-form dynamic linearization (PFDL) data model, and the full-form dynamic linearization (FFDL) data model [Hou and Jin (2011a)]. The controller parameters are then on-line tuned by using the projection algorithm with help of the pre-specified data model.

After years of development, the MFAC is gradually shaped as a systematic work, and has been successfully applied in many specific practical fields, e.g., data dropout compensation control [Pang et al. (2016)], linear motor control [Li et al. (2017)], chemical field [Zhu et al. (2017)], and so on.

Additionally, the bionic robotic fish can only use the energy carried by itself in the moving about underwater, and has the requirement for the longer search distances and longer detection time, thus the energy-saving MFAC (eMFAC) is a great significance for the robotic fish development [Zhi et al. (2001)]. In this paper, an modified MFAC control method, called energy-saving MFAC is proposed for the bionic robotic fish based on the FFDL data model.

The contributions of this paper are as follows. 1) The MFAC is first applied to the control of the bionic robotic fish. The controller structure is determined without any model information of the plant model. 2) By modifying the control criterion function, the energy-saving MFAC(eMFAC) controller is designed to save the energy of the bionic robotic fish.

The rest content is arranged as follows. In Section 2, the dynamics model of bionic robotic fish is formulated. In Section 3, the MFAC and the eMFAC method is detailedly designed. The Section 4 and 5 are simulations and conclusions respectively.

2. BIONIC FISH MODEL FORMULATION

2.1 Three Rigid Bodies Model

In this section, we will first introduce the fish model to explain the fish dynamics, although we do not use it in control system design. The quasi-coordinate Lagrangian method is adopted to model the dynamics of bionic robotic fish with three rigid bodies. The advantage of this method is that the variables are expressed in the body frame, which will reduce the degrees of freedom [Meirovitch and Stemple (1995)].

The three rigid bodies model of the fish is shown in the Fig. 1. The body frame is named as rigid body 0, the left wing is rigid body 1, and the right wing is rigid body 2. The quasi-coordinate Lagrangian equation is

$$\frac{d}{dt} \left(\frac{\partial L}{\partial W} \right) + H \frac{\partial L}{\partial W} = Q \quad (1)$$

where L means the Lagrangian function, namely the total kinetic energy, W is the quasi-velocity, H is a coefficient matrix, Q is a combination of forces and moments, and t is the time.

The dynamics of the fish can be formulated as follows

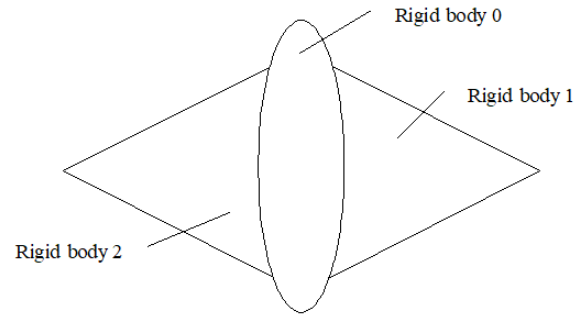


Fig. 1. Three rigid bodies model.

$$\begin{aligned} L &= T_0 + T_1 + T_2 \\ &= \frac{1}{2} m_0 V_0^T V_0 + \frac{1}{2} \omega_0^T I_0 \omega_0 \\ &\quad + \frac{1}{2} m_1 V_1^T V_1 + \frac{1}{2} \omega_1^T I_1 \omega_1 \\ &\quad + \frac{1}{2} m_2 V_2^T V_2 + \frac{1}{2} \omega_2^T I_2 \omega_2 \end{aligned} \quad (2)$$

$$W = [V_0^T, \omega_0^T, \omega_{10}^T, \omega_{20}^T]^T \quad (3)$$

$$H = \begin{bmatrix} \omega_0 & 0 & 0 & 0 \\ V_0 & \omega_0 & 0 & 0 \\ 0 & 0 & \omega_{10} & 0 \\ 0 & 0 & 0 & \omega_{20} \end{bmatrix} \quad (4)$$

$$Q = [F_0^T, M_0^T, M_1^T, M_2^T]^T \quad (5)$$

where T_i ($i = 0, 1, 2$) is the kinetic energy of the rigid body i , m_i is the mass, V_i is the linear velocity, $V_i = [v_{xi}, v_{yi}, v_{zi}]^T$, I_i is the inertia tensor, ω_i is the angular velocity, $\omega_i = [\omega_{xi}, \omega_{yi}, \omega_{zi}]^T$, ω_{10}, ω_{20} are the angular velocities of rigid bodies 1 and 2 respect to rigid body 0, F_0 is the force on the rigid body 0, M_i is the moment on the rigid body i . The more detailed statements can be found in [Meirovitch and Kwak (1992)].

2.2 Hydrodynamic Model

The multiple rigid bodies motion of the bionic robotic fish coupled with complex fluid dynamics requires a reasonable description method. This section introduces a fluid dynamics describing the multiple rigid bodies based on the idea of fluid dynamics modeling of each component. According to the real-time motion state of each body, the hydrodynamic force and moment acting on it are calculated and used to solve the dynamic equation.

The force vector F_i and the moment vector M_i of rigid body i are

$$\begin{cases} F_{ix} = -p(c_{ix} + \Delta c_{ix}) \\ F_{iy} = p(c_{iy} + \Delta c_{iy}) \\ F_{iz} = pc_{iz} \\ M_{ix} = pLm_{ix} \\ M_{iy} = pLm_{iy} \\ M_{iz} = pL(m_{iz} + \Delta m_{iz}) \end{cases} \quad (6)$$

where $p = \frac{1}{2}\rho V_0^2 S$, ρ is the density of sea, S is the reference area, L is the reference length; c_{ix}, c_{iy}, c_{iz} are the resistance, lift and lateral force coefficients of the rigid body i respectively, m_{ix}, m_{iy}, m_{iz} are the roll moment, yaw moment and pitch moment coefficients of the rigid body i respectively. The effect of the tail fin is reflected in $\Delta c_{ix}, \Delta c_{iy}, \Delta m_{iz}$.

The swimming of biological batoid fish depends on flapping and twisting movement of the left and right pectoral fins and flapping movement of tail fin, which will affect the parameters $c_{ix}, c_{iy}, c_{iz}, m_{ix}, m_{iy}, m_{iz}, \Delta c_{ix}, \Delta c_{iy}, \Delta m_{iz}$ in equation (6). Among them, the flapping amplitude of the pectoral fin has a greater effect on the hydrodynamics and the twisting amplitude of the pectoral fin has a smaller effect. In addition, the control frequency and phase difference tend to make the bionic robotic fish unstable. Therefore, considering the flapping amplitude of the pectoral fin β_v as the control input of the forward speed v_{xi} , the movements of left and right pectoral fin are likely. Based on the similar analysis, the yaw angle is controlled by the difference of the flapping amplitude of left and right pectoral fins. The pitch angle of bionic robotic fish is controlled by the flapping amplitude of the tail fin.

3. MODEL-FREE ADAPTIVE CONTROL METHOD AND IT MODIFICATION

From the model description in Section 2.1, we can see that the model of the bionic robotic fish is highly nonlinear and complex, so directly designing the controller based on the simplified model would be not accurate and in a sequel the controller must be a very complex one, which will definitely lead to the difficulties in analysis, diagnosis and applications. In this paper, we will use the FFDL MFAC method to deal with the control system designing issue, instead of the model based control system designing method. The purpose of the research is to demonstrate the alternative robotic fish control method, by which we will show the merit of MFAC for the robotic fish motion control.

As the model of speed and attitude angles are similar, this paper will take the speed as an example. The relationship between the speed v (simplified from v_{x0}) and left pectoral fin angular β_v can be discretized into the following expression

$$v(k+1) = f(v(k), \dots, v(k-n_y), \beta_v(k), \dots, \beta_v(k-n_u)), \quad (7)$$

where k is sampling instant, n_y and n_u denote unknown orders of the system. $f(\dots)$ is an unknown nonlinear function. $v(k)$ is the system output, $\beta_v(k)$ is the control input.

3.1 Prototype of Model-free Adaptive Control

Assumption 1: The partial derivatives of $f(\dots)$ in System (7) with respect to all variables are continuous.

Assumption 2: System (7) satisfies the generalized Lipschitz condition

$$|v(k_1+1) - v(k_2+1)| \leq b \|\mathbf{H}_{L_y, L_u}(k_1) - \mathbf{H}_{L_y, L_u}(k_2)\|$$

where $\mathbf{H}_{L_y, L_u}(0)$ is the initial value of $\mathbf{H}_{L_y, L_u}(k)$. $\mathbf{H}_{L_y, L_u}(k) = [v(k), \dots, v(k-L_y+1), \beta_v(k), \dots, \beta_v(k-$

$L_u+1)]^T \in \mathbb{R}^{L_y+L_u}$ is a vector, which consists of all control input signals between relevant time period $[k-L_u+1, k]$ and all system output signals between relevant time period $[k-L_y+1, k]$. b means a positive constant. L_y and L_u are pseudo order of system (7).

Referred to the assumptions above [Hou and Xiong (2019)], (7) can be converted to the following FFDL data model

$$\Delta v(k+1) = \phi_{L_y, L_u}^T(k) \Delta \mathbf{H}_{L_y, L_u}(k) \quad (8)$$

where $\Delta v(k+1) = v(k+1) - v(k)$, $\Delta \beta_v(k+1) = \beta_v(k+1) - \beta_v(k)$. $\Delta \mathbf{H}_{L_y, L_u}(k) = [\Delta v(k), \dots, \Delta v(k-L_y+1), \Delta \beta_v(k), \dots, \Delta \beta_v(k-L_u+1)]^T$. $\phi_{L_y, L_u}(k) = [\phi_1(k), \dots, \phi_{L_y}(k), \phi_{L_y+1}(k), \dots, \phi_{L_y+L_u}(k)]^T$ is the PG.

The control criterion function is selected as

$$J(\beta_v(k)) = |v^*(k+1) - v(k+1)|^2 + \lambda |\beta_v(k) - \beta_v(k-1)|^2 \quad (9)$$

where $\lambda > 0$ is a weighting constant.

Substituting (8) into (9), then minimizing $\beta_v(k)$ in (9), the controller structure is determined.

$$\beta_v(k) = \beta_v(k-1) + \frac{\rho_{L_y+1} \hat{\phi}_{L_y+1}(k) (v^*(k+1) - v(k))}{\lambda + |\hat{\phi}_{L_y+1}(k)|^2} - \frac{\hat{\phi}_{L_y+1}(k) \sum_{i=1}^{L_y} \rho_i \hat{\phi}_i(k) \Delta v(k-i+1)}{\lambda + |\hat{\phi}_{L_y+1}(k)|^2} - \frac{\hat{\phi}_{L_y+1}(k) \sum_{i=L_y+2}^{L_y+L_u} \rho_i \hat{\phi}_i(k) \Delta \beta_v(k+L_y-i+1)}{\lambda + |\hat{\phi}_{L_y+1}(k)|^2} \quad (10)$$

where $\rho_i \in (0, 1], i = 1, 2, \dots, L_y + L_u$.

Since PG $\phi_i(k)$ is unknown, the following optimization criterion function is given to estimate PG.

$$J(\phi_{L_y, L_u}(k)) = |v(k) - v(k-1) - \phi_{L_y, L_u}^T(k) \Delta \mathbf{H}_{L_y, L_u}(k-1)|^2 + \mu \|\phi_{L_y, L_u}(k) - \hat{\phi}_{L_y, L_u}(k-1)\|^2 \quad (11)$$

where $\mu > 0$ is the weight factor.

From (11), the pseudo-gradient estimation algorithm with some modification for simplicity can be obtained as [Hou and Xiong (2019)]

$$\hat{\phi}_{L_y, L_u}(k) = \hat{\phi}_{L_y, L_u}(k-1) + \frac{\eta \Delta \mathbf{H}_{L_y, L_u}(k-1)}{\mu + \|\Delta \mathbf{H}_{L_y, L_u}(k-1)\|^2} \times (v(k) - v(k-1) - \hat{\phi}_{L_y, L_u}^T(k-1) \Delta \mathbf{H}_{L_y, L_u}(k-1)) \quad (12)$$

where $\eta \in (0, 2]$ is a step size constant. $\hat{\phi}_{L_y, L_u}(k)$ is an estimate of the pseudo-gradient $\phi_{L_y, L_u}(k)$.

The control method introduce a reset mechanism to improve the tracking performance

$$\hat{\phi}_{L_y, L_u}(k) = \hat{\phi}_{L_y, L_u}(1) \quad (13)$$

if $\|\hat{\phi}_{L_y, L_u}(k)\| \leq \epsilon$ or $\|\Delta \mathbf{H}_{L_y, L_u}(k-1)\| \leq \epsilon$, or $\text{sign}(\hat{\phi}_{L_y+1}(k)) \neq \text{sign}(\hat{\phi}_{L_y+1}(1))$, where $\epsilon > 0$ is a small positive constant.

3.2 Energy Saving Model-free Adaptive Control

For the bionic robotic fish, choosing $L_y = 3, L_u = 1$, then the FFDL-MFAC data model (8) is written as

$$\Delta v(k+1) = \phi_1(k)\Delta v(k) + \phi_2(k)\Delta v(k-1) + \phi_3(k)\Delta v(k-2) + \phi_4(k)\Delta\beta_v(k) \quad (14)$$

To reduce the energy consumption of the bionic robotic fish, the control criterion function is redesigned as

$$J(\beta_v(k)) = [v^*(k+1) - v(k+1)]^2 + \lambda_1\Delta\beta_v^2(k) + \lambda_2\beta_v^2(k) \quad (15)$$

where $\lambda_1 > 0, \lambda_2 > 0$.

Then substituting (14) into (16) and minimizing $\beta_v(k)$ in (16), the controller of eMFAC can be written as

$$\begin{aligned} \beta_v(k) = & \frac{\lambda_1 + \hat{\phi}_4(k)^2}{\lambda_1 + \lambda_2 + \hat{\phi}_4(k)^2} \beta_v(k-1) \\ & + \frac{\hat{\phi}_4(k)\rho_3 (v^*(k+1) - v(k) - \rho_1\hat{\phi}_1(k)\Delta v(k))}{\lambda_1 + \lambda_2 + \hat{\phi}_4(k)^2} \\ & - \frac{\hat{\phi}_4(k) [\rho_2\hat{\phi}_2(k)\Delta v(k-1) + \rho_3\hat{\phi}_3(k)\Delta v(k-2)]}{\lambda_1 + \lambda_2 + \hat{\phi}_4(k)^2} \end{aligned} \quad (16)$$

where $\rho_i \in (0, 1], i = 1, 2, 3, 4$.

The estimation criterion function of PG vector is:

$$\begin{aligned} J(\phi_{3,1}(k)) = & |v(k) - v(k-1) - \phi_{3,1}^T(k)\Delta\mathbf{H}_{3,1}(k-1)|^2 \\ & + \mu \left\| \phi_{3,1}(k) - \hat{\phi}_{3,1}(k-1) \right\|^2 \end{aligned} \quad (17)$$

Minimizing (18) and using a similar modification procedure like in Section 3.1 above, the pseudo-gradient estimation algorithm is constructed as follows

$$\begin{aligned} \hat{\phi}_{3,1}(k) = & \hat{\phi}_{3,1}(k-1) \\ & + \frac{\eta\Delta\mathbf{H}_{3,1}(k-1)(v(k) - v(k-1))}{\mu + \|\Delta\mathbf{H}_{3,1}(k-1)\|^2} \\ & - \frac{\eta\Delta\mathbf{H}_{3,1}(k-1)\hat{\phi}_{3,1}^T(k-1)\Delta\mathbf{H}_{3,1}(k-1)}{\mu + \|\Delta\mathbf{H}_{3,1}(k-1)\|^2} \end{aligned} \quad (18)$$

where $\eta > 0, \hat{\phi}_{3,1}(k)$ is an estimate of the pseudo-gradient $\phi_{3,1}(k)$.

A reset mechanism is

$$\hat{\phi}_{3,1}(k) = \hat{\phi}_{3,1}(1) \quad (19)$$

if $\left\| \hat{\phi}_{3,1}(k) \right\| \leq \varepsilon$ or $\|\Delta\mathbf{H}_{3,1}(k-1)\| \leq \varepsilon$, or $\text{sign}(\hat{\phi}_3(k)) \neq \text{sign}(\hat{\phi}_3(1))$, where ε is a small positive constant.

Remark 1. The design method of eMFAC is to add $\beta_v^2(k)$ to the control input criterion function, so that the control input $\beta_v(k)$ will not be too large. In addition, it means that $\beta_v(k)$ will not touch the upper and lower boundaries very often, and changes more smoothly. In other words, the actual actuator does not oscillate too often. eMFAC is designed to reduce the energy consumption of control input $\beta_v(k)$. By controlling the amplitude variation of the input, the amplitude accumulation becomes smaller and the energy required to produce the input for the whole system is correspondingly reduced.

4. SIMULATION RESULTS

Because PID controller is simple and efficient, and is widely used in practical industrial environment, therefore, it is selected as to compare the control performance of MFAC controllers and the eMFAC controller. To better simulate the complexity of underwater environment, the north flow velocity 0.4m/s and the vertical flow velocity 0.3m/s are added as the disturbance factors. The following simulation results for both control methods are all performed under the same perturbation conditions.

In order to adapt to various task requirements, the expectation curve adopted here is square wave. Due to the unique combination movement of flapping (up and down) and twisting (back and forth), the hydrodynamic force and moment are very complex. In addition, considering the actual movement ability of the pectoral fin and tail fin, the control interval is chosen as 0.5s, which made the speed and attitude angle of the bionic robotic fish have inevitable small amplitude oscillation in the whole process.

The parameters of speed controller and yaw angle controller are shown in the table 1-table 3.

Table 1. Parameters of PID

Parameters	Speed Control Value	Yaw Angle Control Value
k_P	3	0.92
k_I	1	0.3
k_D	0.5	0.2

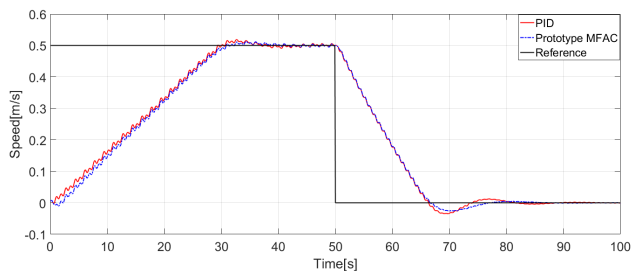
Table 2. Parameters of Prototype MFAC

Parameters	Speed Control Value	Yaw Angle Control Value
ρ_1	3	1
ρ_2	1	0.5
ρ_3	1	0.5
ρ_4	0.8	1
λ	0.5	0.1
μ	1	1
η	2	1
ϕ	[1,1,1]	[1,1,1]

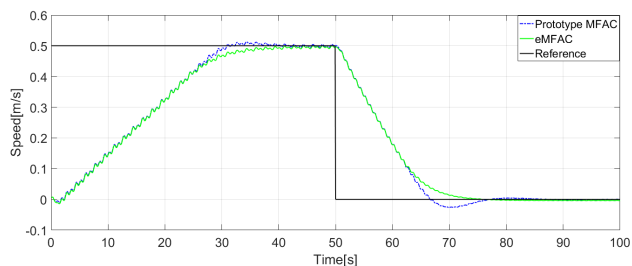
Table 3. Parameters of eMFAC

Parameters	Speed Control Value	Yaw Angle Control Value
ρ_1	3	1
ρ_2	0.8	0.3
ρ_3	0.8	0.5
ρ_4	0.4	0.4
λ_1	0.03	0.1
λ_2	0.003	0.0001
μ	1	1
η	1.8	1
ϕ	[1,1,1]	[1,1,1]

The simulation comparison results between PID, MFAC and eMFAC of speed controller are shown in Fig. 2-Fig. 3. PID parameter has been adjusted to the best control effect. It can be seen from the simulation results that both of them can achieve acceptable performances with small tracking error. However, the performance of MFAC is superior to that of PID in the overshooting and setting time. In addition, the eMFAC has almost no overshoot compared with MFAC and PID, although its response time is slightly slower.

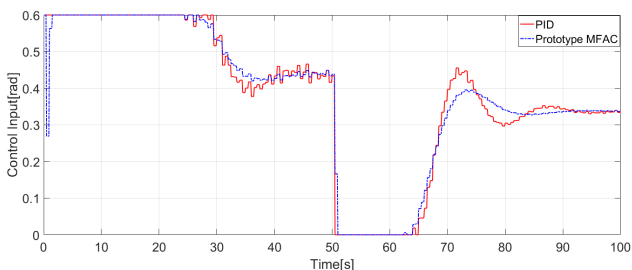


(a) Tracking performance

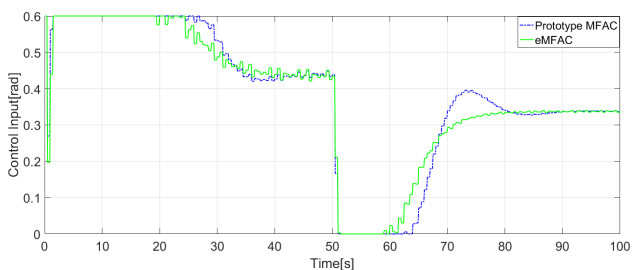


(b) Tracking performance

Fig. 2. Speed control



(a) Control input

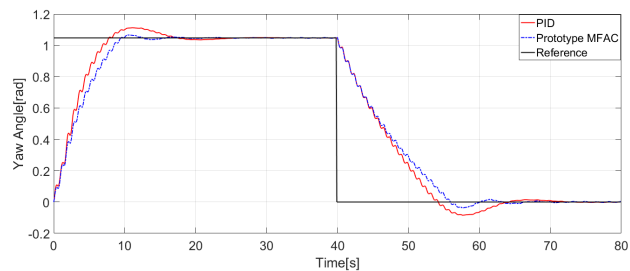


(b) Control input

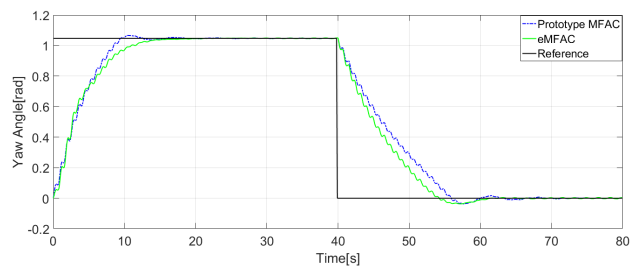
Fig. 3. Speed control

The simulation comparison results between PID, MFAC and eMFAC of yaw angle controller are shown in Fig. 4- Fig. 5. The eMFAC achieves a better control performance comparing to that of prototype of FFDL-MFAC, and the fluctuation of control input is smaller than that of the prototype as well. So the whole process amplitude accumulation is smaller, and the energy consumption is lower.

The sum of the control inputs required to achieve the value of expectation at the same time is used to measure the energy consumption, defined as $\text{sum} = \sum_0^t u(k)$, where t is time, $u(k)$ is the value of the control input at each discrete

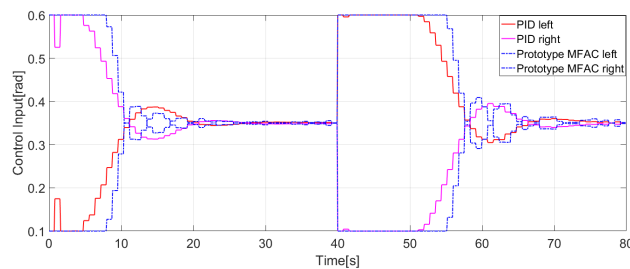


(a) Tracking performance

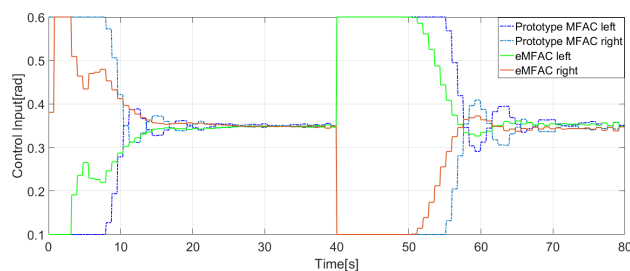


(b) Tracking performance

Fig. 4. Yaw angle control



(a) Control input



(b) Control input

Fig. 5. Yaw angle control

time in time t . After calculation, the energy consumed by different control algorithms to control the speed and yaw angle is shown in the table 4.

Table 4. Cumulated Value of Energy

Control Algorithm	Speed Control	Yaw Angle Control
<i>PID</i>	382.8418	299.1570
<i>MFAC</i>	383.2084	298.8292
<i>eMFAC</i>	379.8317	297.5724

Remark 2. MFAC can theoretically guarantee the stability of the controlled object and can produce better control effect [Hou and Xiong (2019)]. The design of MFAC controllers is simpler and easier to understand than methods

such as neural networks. MFAC controller design is slightly more complex than PID, but the parameters of MFAC are adjusted automatically, rather than PID manually.

5. CONCLUSION

In this paper, the full form dynamic linearization data model based model-free adaptive control method is applied to the control of bionic robotic fish and further, the prototype MFAC scheme is modified by extra adding a new punishment term in the control input cost function, which will constraint the energy consumption. Furthermore, the designed controller is model-free and only needs the I/O data to calculate the control input and pseudo-gradient vector. The simulation results are given to demonstrate the advantages of the proposed control method. In near future, we will put it into a practical application on a lab robotic fish under some water.

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