Biomimetic Underwater Vehicle Modeling Based on Neural Network

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Abstract: This paper introduces the basic control methods of a Biomimetic Underwater Vehicle, and a neural network model is designed for the vehicle. The concerned vehicle is propelled by two undulating long-fins installed on both sides. Ten motors are employed to drive the long-fin and sine wave function is employed for motor control. The real-time control system is designed for controlling the long-fins by adjusting its oscillating frequency and oscillating amplitude to control the yaw angle of the vehicle. A set of inertial sensors is employed for collecting pose information including yaw angle. Analyses show that the yaw angle increment is closely related to the long-fin oscillating frequency, the long-fin oscillating amplitude and the vehicle yaw angle velocity. Hence a neural network with one hidden layer is designed for building a nonlinear MISO model. Based on qualitative hydrodynamic analysis, oscillating frequency of the two long-fins and angular velocity are chosen as the model input. And the yaw angle increment is chosen as the model output. Based on analysis of the experimental thrust data, linear function is used as activation function of the neurons. Finally, experimental data are used for neural network training and validation. The results show that the designed neural network model is valid.

Keywords: Biomimetics, underwater vehicle, system identification, neural network.

1. INTRODUCTION

In recent years the developments of biomimetic robotic fish have generated a significant interest in the field of Biomimetic Underwater Vehicles (BUV). Driven by the demands of applications in complex underwater circumstance, many researchers have borrowed ideas from the special propulsion systems of fishes. In nature, there are two basic swimming styles: body and/or caudal fin (BCF) locomotion and median and/or paired fin (MPF) locomotion (Drucker et al., 2005). By contrast, MPF locomotion has more excellent manoeuvrability, flexibility and stabilization. Hence we design a biomimetic underwater vehicle which employs MPF locomotion and has two undulating long-fins.

Recently, due to differential demands in practical applications, close-loop control for a BUV is more important. Therefore, many researchers have done a lot of work in motion control and modeling for biomimetic underwater vehicles. General motion control strategies only focused on gait, which belongs to open-loop control with respect to the whole system (Triantafyllou et al., 2000; Ernest et al., 2008). And some other researchers employ CPG(Central Pattern Generator)-based control algorithm and may use a Microprogrammed Control Unit (MCU) to achieve simple locomotion control by tuning CPG parameters (Matsuo et al., 2007). With the developments of high-speed vision sensor, vision-based control system for robotic fish is also used for swimming control (Yu et al., 2007). Obviously, there has been a lot of modeling work based on the BUV architecture.

Hydrodynamic force analysis modeling algorithms belong to very popular and staple methods (Lighthill et al., 1990; Lauder et al., 2007; Willy et al., 2005). MacIver et al proposed an idealized ellipsoidal body model based on Kirchhoff’s equations, which treated robotic fish as a rigid ellipsoid (MacIver et al., 2004). And according to the underwater robotic vehicle with three-layer structure, some researchers proposed according modeling algorithms (Zhang et al., 2009). Aiming at the special design architecture, some other modeling algorithms are also proposed (Morgansen et al., 2007; Boyer et al., 2006). Though the researchers have done significant works on modeling for BUV, there are still a lot of works to do. As mentioned, most of the modeling algorithms are based on hydrodynamics. The algorithms assume that the circumstance BUV works is ideal fluid and also assume the characters of BUV do not change. Obviously, they are impossible in practical application.

In this paper, our underwater vehicle hardware design has two divided parts: driving system and control system. The driving system is in charge of producing pulse width modulation (PWM) signals for the two long-fins. And the control system is in charge of adjusting the oscillating frequency, oscillating amplitude of each long-fin. It also includes the sensor information collection system which is used to process the yaw angle data etc. Based on a lot of experimental data including yaw angle output and relevant inputs of the two long-fins, a algorithm based on neural network (NN) is proposed for system modeling. The neural network has one hidden layer. According to hydrodynamic analysis, the oscillating frequency/amplitude of the left long-
fin and the right long-fin, and the instantaneous angular velocity are chosen as model input. And the yaw angle increment is chosen as model output. Based on thrust experimental results, linear function is used as activation function for the neural network layers. And the yaw angle increment estimation may be carried out on-line because of less calculation.

The remainder of this paper is organized as follows. Section 2 introduces the vehicle prototype and system architecture. Section 3 presents the adjusting method for the two long-fins. The neural network model is described in section 4. Section 5 describes the results of neural network training and model validation. Finally the conclusion is given in section 6.

2. VEHICLE PROTOTYPE AND SYSTEM DESIGN

2.1 Biomimetic Underwater Vehicle Prototype

The Fig. 1(a) shows a prototype of the underwater vehicle and Fig. 1(b) shows the long-fin. The vehicle consists of a rigid body and two long-fins.

![Fig. 1. (a) Prototype of the vehicle. (b) Long-fin.](image)

Rigid body of our underwater biomimetic vehicle is made of glass fiber reinforced plastic and ten servo-motors are installed on each side which is used to drive the long-fin. As shown in Fig. 1 (b), each long-fin is a skeleton covered by soft, elastic membrane. Ten fin-rays connected with the servo-motors are distributed symmetrically in the membrane. Therefore, different control strategies will make the fin-ray oscillating to generate thrust and torsional moment. Obviously, coordination control of the two long-fins may generate different locomotion.

2.2 System Architecture Design

Our vehicle system hardware design may be separated into three parts: control system, driving system and other accessories. The driving system is in charge of generating PWM signals for the servo-motors on the each long-fin. And the control system processes external information and sends control command for driving system. The whole system design is shown in Fig. 2.

![Fig. 2. System architecture.](image)

External command module is designed for wireless command reception in remote manual control. And the inertial sensor system is integrated in the vehicle system. Both the modules are based on interrupt mechanism, which ensures the quick-response character of the vehicle. The control system receives and processes the data from the two modules mentioned above and then computes the control increments, namely the frequency/amplitude of the two long-fins. In addition, multi-thread synchronization method is used in the control system to ensure real-time control. Finally, the control increments are sent to the driving system. A modified embedded Linux OS is selected for the control system and the driving system is developed on the basis of (Field-Programmable Gate Array)FPGA technology.

A protocol is designed for communication between the control system and the driving system. And the driving system employs parallel processing method in order to ensure that the vehicle control is hard real-time.

3. OSCILLATING CONTROL ALGORITHMS FOR THE TWO LONG-FINS

As mentioned above, sine wave function is employed for the control of each fin-ray. Define the oscillating frequency as \( f \), oscillating amplitude as \( A \) and the instantaneous phase as \( \phi \). The oscillating function is shown as follows:

\[
\phi = A \sin(2\pi ft + \phi)
\]
Where $\phi$ is the initial phase and $t$ is the time. Obviously, the ten fin-rays according to different instantaneous phases bend the long-fin into the corresponding wave form. Then the undulating long-fin makes the vehicle move forward. Therefore the adjacent fin-rays have same phase difference, which equal to $2\pi/9 \times (2\pi/(10-1))$. Therefore, the oscillating function for each fin-ray may be expressed as:

$$\phi_i = A \sin(2\pi f t + (i-1) \times 2\pi/9)$$  \hspace{1cm} (2)

From (2), $f$ and $A$ decide the oscillating mode of the long-fin. Obviously, different values of $f$ and $A$ of the two long-fins may generate varied locomotion. When the torsional moment supplied by the two long-fins is not equal, the vehicle will make turning locomotion. Therefore, adjusting algorithms of the frequency and amplitude are the first stone to control the long-fins in practical applications.

### 3.1 Frequency Adjusting Method

As shown by (2), the oscillating frequency is one factor affected the vehicle locomotion. Different oscillating frequency of the two long-fins has an important influence on the vehicle’s yaw angle and velocity. Therefore, frequency adjusting algorithm is necessary for motion control.

The vehicle’s frequency adjusting is related to three aspects closely. Firstly, increment control for servo motor is employed to achieve the predetermined oscillating frequency. For the driving system based on FPGA, rounding error is an important error source to oscillating frequency adjusting. With the rounding error accumulating, the oscillating wave form of the ten fin-rays will not keep sine discipline. And this situation may bring the long-fin uncertain and unexpected oscillating. Secondly, the adjusting algorithm should be real-time to guarantee system performance. Obviously, system identification for the vehicle depends on real and reliable data, which should be collected real-time. Thirdly, the control system of the vehicle sends frequency increment to the driving system for controlling the two long-fins, and the driving system must assign the relevant increment to each motor and drive the motors.

Based on the above analyses, relevant methods are proposed. Though the servo-motor oscillating is based on discrete control, one special strategy is used in our vehicle which forces each servo-motor to stop at “zero position” in continuous control. Then, the following control method may be presented. For each servo-motor, frequency adjusting only starts at the “zero position”. Obviously, though frequency adjusting command happens at different amplitude of each servo-motor, the real adjusting process always begins when each servo-motor reach its “zero position”. And the relevant fin-rays keep their original oscillating disciplines before adjusting process begins. This method eliminates the rounding error accumulation in the FPGA-based driving system. And a monitor is employed in the driving system. Once a command is received, interrupt occurs and adjusting process begins. For all the adjusting processes of the servo-motors are carried out in parallel, the response time limits as less than 1 ms. Meanwhile, according to the predefined protocol, the driving system can distinguish the control commands including frequency increase, left long-fin, right long-fin etc. And the frequency increases are assigned and sent for driving the relevant servo-motors. Fig. 3 shows the adjusting processing of three fin-rays for oscillating frequency.

![Fig. 3. Frequency adjusting for the long-fin.](image)

### 3.2 Amplitude Adjusting Method

Another factor affected the vehicle locomotion in (2) is the oscillating amplitude of the two long-fins. Obviously, well-chosen oscillating amplitude may make the vehicle more maneuverable.

Similar to frequency adjusting, there also exists rounding error in the FPGA-based driving system. The difference lies in other two aspects. One is that the membrane will limit the amplitude of the fin-ray oscillating if the adjacent fin-ray has large phase difference in some swimming locomotion. And this may change the stable phase difference between adjacent fin-ray. Another is that the driving system may generate uncertain behavior when amplitude adjusting and frequency adjusting occur at the same time. These two reasons result to the difference between frequency adjusting and amplitude adjusting.

As mentioned above, amplitude adjusting may leads to phase difference change between adjacent fin-rays, which disarranges the oscillating discipline of the long-fin. In this paper, a phase difference adjusting method is given. As shown by (2), the phase difference between adjacent fin-ray has stable value. Therefore, if the adjusting command is received, adjusting process of each fin-ray starts. Next, define the first fin-ray as the standard fin-ray. When the second fin-ray reaches at “zero position” and it will adjust the phase difference according to the first fin-ray. Then the third fin-ray adjusts the phase difference according to the second one by same way, and so on. Therefore, all the phase difference adjusting may end in the following 4.5 clock cycles. And Fig.
4 shows the phase difference adjusting process of the first three fin-rays in amplitude adjusting.

![Fig. 4. Phase difference adjusting for fin-rays.](image)

4. NEURAL NETWORK MODEL FOR UNDERWATER BIOMIMETIC VEHICLE

Yaw angle modeling for BUV acts as an important role in vehicle navigation. One well-suited model may improve navigation control algorithm a lot. Traditional yaw angle modeling algorithms are mostly based on hydrodynamic analysis, which may be not very suitable in nonideal fluid in practical applications. Therefore, system identification based on real-time sensing data has stronger application prospect.

4.1 Force Analysis for the Vehicle

The swimming vehicle acts on the water with several main forces: gravity $G$, buoyancy force $F_b$, water resistance in swimming direction $F_h$, thrust by left long-fin $F_{left}$, thrust by right long-fin $F_{right}$, and water resistance in section direction $F_w$. Fig. 5 shows the forces acted on the vehicle in water.

![Fig. 5. Forces acted on the underwater vehicle.](image)

Here, $F_w$ is generated when $F_{left}$ is not equal to $F_{right}$. Obviously, there are three factors having influence on yaw angle, which are $F_{left}$, $F_{right}$ and $F_w$. $F_{left}$ and $F_{right}$ are generated by the two long-fins and controlled by the oscillating frequency and oscillating amplitude of the long-fin. And the direct influence on $F_w$ is the angular velocity through force analysis.

For simplification, a stable value is chosen as the oscillating amplitude of the two long-fins. Therefore, the yaw angle model chooses three parameters as model inputs, which are the oscillating frequency of each long-fin, the angular velocity.

4.2 Neural Network Structure

As mentioned in 4.1, the three system inputs represent the hydrodynamic forces. As known, hydrodynamic analysis is very complex, and the relation between the system inputs and yaw angle output is nonlinear. Therefore, a neural network model is proposed for the BUV.

In this paper, a neural network structure with one hidden layer is employed, shown by Fig. 6.

![Fig. 6. Neural network with one hidden layer](image)

Where, $b_b$ and $b_w$ are the input bias of hidden layer and output layer, $\sigma_l$ is the hidden layer neural, $x_{in1}$, $x_{in2}$, $x_{in3}$ is the three system inputs and $\Delta\theta$ donates the system output which is the yaw angle increasement. And $V_{ij}$ and $W_{jk}$ are the weight matrix of the two adjacent layers separately.

Another important factor of neural network is the choice of activation function. In previous experiments, the relationship between the oscillating frequency of the long-fin and thrust has been studied, shown by Fig. 7. Due to mechanism limit and serve motor limit, the oscillating frequency of the long-fin is limited to the range of [1HZ, 3HZ].
In Fig. 7, the nonlinear character between the thrust and oscillating frequency is not very strong. Therefore, “purelin” linear activation function for neural network is employed in this paper, as follows.

\[ Y = T \cdot X \]  

(3)

Where \( Y \) is the output of hidden layer/output layer, \( T \) is the relevant weight matrix and \( X \) is the relevant neural network input vector.

4.3 Online Back Propagation Learning NN Adaptation

Back propagation learning is a staple leaning algorithm for neural network. For online system identification, one reasonable choice for this learning law is to train the neural network based on previously stored control information. In this paper, same adaptive learning law is employed in hidden layer and output layer, which is an approach to utilize the experimental data as online weight matrix adaption in back propagation learning neural network adaption.

All the stored system inputs achieved in experiments are equally considered and sent to neural network in turn. Then the hidden layer output of the model may be achieved by summing with the learning adaption. The output layer output of the model is achieved by same way. Next, according to the model output of output layer and real measured output, the model tracking error is gotten. Neural network employs function of tracking error as learning performance \( \dot{\zeta} (n) \), as follows.

\[ \dot{\zeta} (n) = 1/2 \cdot \dot{\varepsilon}^2 (n) \]

\[ \varepsilon (n) = y_{\text{real}} (n) - y_{\text{model}} (n) \]  

(4)

The weight matrix of output layer and hidden layer updates in same way, shown in (5).

\[ \Delta W(n) = \alpha \cdot \Delta W(n-1) + \eta \cdot \delta(n) \cdot y(n) \]

\[ W(n + 1) = W(n) + \Delta W(n) \]  

\[ y(n) = \sum_i (W_i (n) \cdot x_i (n)) \]  

(5)

Where a study factor \( \eta \) is set to change the study speed and another stable factor \( \alpha \) is set to make the neural network more stable. \( x_i (n) \) is neural network model input of output layer/hidden layer, and \( \delta(n) \) is the relevant local gradient.

For output layer, \( \delta_{\text{output}} (n) \) may be gotten by (6). And for hidden layer, \( \delta_{\text{hidden}} (n) \) may be gotten by (7).

\[ \delta_{\text{output}} (n) = \varepsilon (n) \cdot \psi' (v_j (n)) \]

\[ v_j (n) = \sum_i \delta (n) \cdot W_{ji} (n) \]  

(6)

\[ \delta_{\text{hidden}} (n) = \psi' (v_j (n)) \sum_i \delta_{\text{output}} (n) \cdot W_{ji} (n) \]

\[ v_j (n) = \sum_i \delta (n) \cdot V_{ji} (n) \]  

(7)

Where \( \psi() \) is the activation function of output layer/hidden layer.

5. EXPERIMENTS AND MODEL VALIDATION

In this section, experiments are divided into two parts. One part of experiments is carried out to achieve relevant experimental data for modeling. And another part of experiments is carried out to validate the model. And the discussion is given finally.

5.1 Experiments for Modeling

As mentioned in section 2, the real-time control system sends the relevant frequency adjusting command to the driving system. Meanwhile, the inertial sensor information and instantaneous oscillating frequencies of both long-fins are recorded in a file. Therefore, all the information required for system identification may be gotten.

In experiments, the oscillating frequency of the left long-fin and right long-fin keeps in range of [0.96HZ, 2HZ], which is shown in Fig. 7. The instantaneous angular velocity and yaw angle increasement are measured by inertial sensor system.
For the designed neural network model, the neural number in the middle layer is 8. \( b_v \) and \( b_w \) are set to stable value 1. \( x_{o1}, x_{o2}, x_{o3} \) is the oscillating frequency of the left long-fin, the frequency of the right long-fin and the angular velocity of the vehicle. And the system output is chosen as yaw angle increaseamnt. After 100 back propagation learning neural network adaptation for weight matrix, the tracing error is limited to 0.00954. And Fig. 8 shows the neural network train process.

5.2 Model Validation

The experiment for the neural network model validation is carried out. And the model validation result and the model error are shown in Fig. 9 and Fig. 10.

![Model Test](image_url)

Fig. 9. Model validation.

![Model Test](image_url)

Fig. 10. Model validation error.

In Fig. 9, the model outputs are similar to the measured data, which shows the neural network model is suitable for the vehicle. And Fig. 10 shows that the model error is acceptable. In addition, the online model identification method employs linear function as activation function which costs less computation power. Therefore, the proposed modeling method is suitable for real-time control.

6. CONCLUSIONS

System architecture design for a biomimetic underwater vehicle with two undulating long-fins is proposed. According to the demands for navigation, oscillating frequency and amplitude adjusting algorithms are given. The vehicle employs inertial sensors to achieve pose information. And according to thrust experiments result, yaw angle model identification method with a neural network is proposed. Finally, experiments results show our method is valid and suitable for real-time navigation control.

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