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A Bionic Neural Network for Fish-Robot Locomotion

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Abstract

A bionic neural network for fish-robot locomotion is presented. The bionic neural network inspired from fish neural network consists of one high level controller and one chain of central pattern generators (CPGs). Each CPG contains a nonlinear neural Zhang oscillator which shows properties similar to sine-cosine model. Simulation results show that the bionic neural network presents a good performance in controlling the fish-robot to execute various motions such as startup, stop, forward swimming, backward swimming, turn right and turn left.

Keywords: neural network, central pattern generators, nonlinear oscillator, swimming locomotion, fish-robot

1 Introduction

Most of current fish-robots are inspired from the aquatic animals especially fishes and designed for various purposes, such as entertainment, exploration, transportation, and medical treatment[1]. The control systems which consist of micro-processors, functional units, and electric circuits are quite different from the neural network of animals and contrasted obviously with other similarities of shape, structure, locomotion styles and so on. The locomotion gaits are distilled from the experimental observations of fish locomotion. An high level controller plays the exclusive role of gaits generation and takes charge of gaits distribution to all joints[2–4]. It is quite different from the mechanism of the real animal neural network for locomotion. The animal locomotions are not only modulated by the advanced neural central system but also controlled by the local neural network called central pattern generators (CPGs) which are located in spinal cord. The serial studies on lamprey indicated that the CPGs can not only sustain the rhythmic locomotion but also coordinate segmental and intersegmental locomotion with sensor feedback and are adaptive with environmental change[5–7].

The purpose of this paper is to develop a bionic neural network for fish-robot locomotion. The bionic neural network consists of one high level controller and one chain of CPGs which are composed of coupled nonlinear artificial neural oscillators. It has many similarities with neural network of fish, such as "fictive locomotion", startup or stop of swimming, turning, and intersegmental coördination. The validity in the control of fish-robot locomotion is proved by the simulation results.

We presented our studies in the following four sections. First, the principles of the neural network for fish locomotion are analyzed in section 2. Then, a bionic neural network for fish-robot locomotion is proposed in section 3. In section 4, the experiment results of the bionic neural network are given in various motions. In the section 5, the conclusion is briefly summarized.

2 Neural network for fish locomotion

Fish locomotion can be classified into two generic categories: the periodic (steady or sustained) swimming and the transient (unsteady) movement[8]. The periodic swimming is characterized by the repetition of the propulsive movement and is employed by fish to cover long distance at a more or less constant speed. It has been the centre of scientific attention among biologists and en-

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gineers because that it is the dominating locomotion method used by fish and fish-robots. Most fishes generate thrust by bending their bodies into a backward-moving propulsive wave that extends to its caudal fin, a type of swimming classified under body and/or caudal fin (BCF) locomotion. Other fishes have developed alternative swimming mechanisms that involve the use of their median and pectoral fins, termed median and/or paired fin (MPF) locomotion[9]. The swimming modes associated with BCF propulsion and MPF propulsion were described in detail by Lindsey [10].

We only concentrate on the neural network for propulsors which induce the main thrust, therefore, the delicate controls of pectoral fins, pelvic fins, anal fins which associated with the maneuverability of fish are beyond the scope of this paper.

Most fishes belong to vertebrate for their distinct backbones in the middle axis of body, and the neural network tissue which is located in the backbones called "spinal cord". Both of the BCF locomotion and MPF locomotion are belong to the rhythmic locomotion from the view of biologists. Rhythmic locomotion is produced by central pattern generating network whose outputs are shaped by sensory and neuromodulatory inputs to allow the animal to adapt its locomotion to changing needs[11-13]. The neural circuitry of lamprey has been worked out in experiments [5, 14] and the evidence for CPGs governing locomotion were reviewed by Lyons[15].

It is difficult to record the detailed interactions among the neurons in the neural network by equipments due their inherent nonlinear properties, micro-scale, complicated coupling and huge number of neurons and so on. A perfect and complete mathematical model to describe the dynamics of the neural network for locomotion is almost impossible.

We proposed a general neural network for fish locomotion which is shown in Fig. 1. The supraspinal inputs from cerebrum tissue play the major roles not only in initiating or ceasing locomotion but also in adapting the locomotor patterns to environmental and motivational conditions. The two CPGs located in the same segment of spine cord have reciprocal inhibitory connections and can stimulate the muscles to contract or stretch alternately. When one side is contracted, the opposite side muscle is stretched and the stretch receptor is activated. Then the activated stretch receptor stimulates the activated CPG to inhibition, and stimulates the opposite side CPG to be activated which stimulates the opposite side muscle to contract in turn.

The intersegmental connections mainly are the descending channels which transfer the commands from cerebrum tissue to each CPG in all segments[16]. The lag time of adjacent segments can vary from several seconds during very slow swimming to as quick as one percent of a second for sudden sprint. But the intersegmental phase lag remains fixed in spite of time variety to sustain a steady waveform along the fish body. The neural network can easily produce reverse patterns for backward swimming by switching the transfer direction.

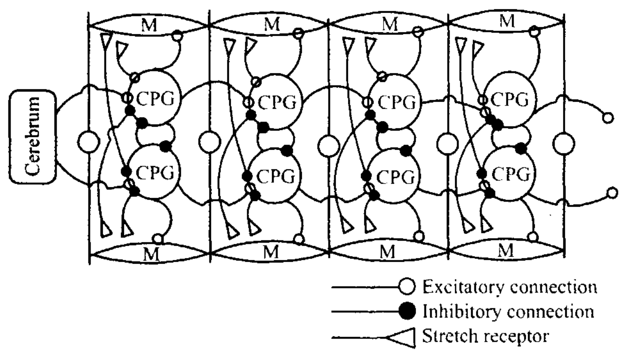


Fig. 1 Neural network for fish locomotion, "M" denotes the muscle in the both sides.

3 Design of bionic neural network

3.1 Neural oscillator based on sine-cosine model

The CPG is often modelled as a neural oscillator with intersegmental descending command and segmental sensor feedbacks. Wilson and Cowan[17] proposed a famous oscillator in 1972 which has been widely adopted in bionic robot control[18,19]. Matsuoka[20] proposed an particular artificial neural oscillator composed of four neurons to imitate the symmetry inhibitory properties. The Matsuoka oscillator's frequency and amplitude can be modulated by manual setting of the dynamic functional parameters. But the process can not be autonomously carried through for the nonlinear relations between them.

We have proposed an artificial neural oscillator (Zhang oscillator) based on sine-cosine model[21]. Our oscillator as shown in Fig. 2 has much comparability with the Wilson-Cowan oscillator.

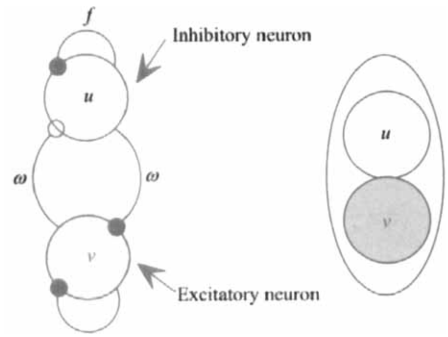


Fig. 2 Zhang oscillator.

The dynamics of Zhang Oscillator can be described by the following differential equations:

$$\begin{cases} \dot{u} = \omega v + f(u) \\ \dot{v} = -\omega u + f(v) \end{cases}, \tag{1}$$

where u and v denote the inhibitory and excitatory neuron activities, respectively, ω is a parameter which mainly determines the angular frequency of oscillation, and $f(x)$ is a nonlinear function. If we set the nonlinear function to be zero in all time, then the system becomes the general sine-cosine oscillation which is written as

$$\begin{cases} \dot{u} = \omega v \\ \dot{v} = -\omega u \end{cases}. \tag{2}$$

If the initial condition is given as

$$\begin{cases} u(t=0) = u_0 \\ v(t=0) = v_0 \end{cases}, \tag{3}$$

thus the global solution of the system is obtained as

$$\begin{cases} u(t) = \sqrt{u_0^2 + v_0^2}\sin(\omega t + \phi_0) \\ v(t) = \sqrt{u_0^2 + v_0^2}\cos(\omega t + \phi_0). \\ \phi_0 = \tan^{-1}(u_0, v_0) \end{cases} \tag{4}$$

The original sine-cosine oscillation is unsteady with disturbing inputs for its lack of limit cycles in phase plane.

The nonlinear function we chosen in Zhang oscillator is composed of a negative linear part and a nonlinear anti-tangent part. It is described in the following equation:

$$f(x) = k\left(-\frac{x}{r} + \frac{4}{\pi}\tan^{-1}\left(\frac{x}{r}\right)\right), \tag{5}$$

where k denotes the sustain strength of limit cycles, and r denotes approximately radius of the limit cycles. The whole dynamics of Zhang oscillator composed of Eq. (1) and (5) can be described by the following equations:

$$\begin{cases} \dot{u} = \omega v + k\left(-\frac{u}{r} + \frac{4}{\pi}\tan^{-1}\left(\frac{u}{r}\right)\right) \\ \dot{v} = -\omega u + k\left(-\frac{v}{r} + \frac{4}{\pi}\tan^{-1}\left(\frac{v}{r}\right)\right) \end{cases}. \tag{6}$$

The limit cycle forming process in Zhang oscillator is shown in Fig. 3. The original point $O(0,0)$ is the sole balance point which gets away from the attraction of the limit cycles. But it is still an unsteady point which can be pushed away with only a little disturbing signal and falls down to the limit cycles quickly.

The Zhang oscillator has many convenient control properties for its decomposition of parameters in nonlinear function, in contrast to the composition of Wilson-Cowan oscillator. It makes the modulation of each parameter of the oscillation to be realizable.

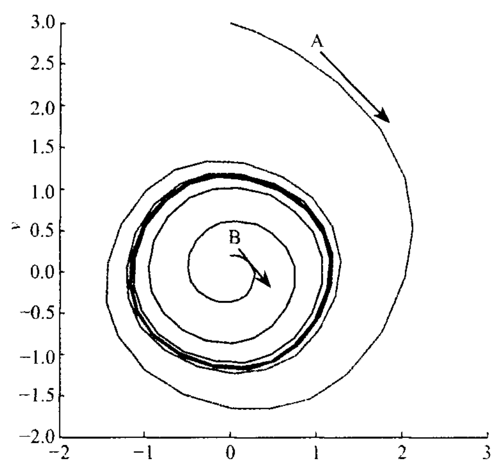


Fig. 3 Limit cycles of Zhang oscillator in u–v phase plane, with $k = 5$, $r = 1$ and $\omega = 2\pi$.

3.2 Design of segmental CPG

The biologic neurons in negative activity status can not stimulate the muscles to contract or stretch. Although it has the ability to produce periodic changing activity signals, a single CPG in negative activity means losing control to the other CPG neurons or muscles. So the biologic neural network in each spine cord segment consists of two CPGs to control the right side and left side muscles, respectively. But there are no such actuators like muscles available in the fish-robot. The common actuators in fish-robot are different motors or motor-gearbox composition instruments. We suppose that there is one motor mounted in the body axis joint and it can be controlled by local micro-processor unit distributed in each segment. So it is effective and economical to design one CPG to control the motor's movement.

We designed a segmental CPG based on Zhang oscillator as illustrated in Fig. 4. The dynamics of the segmental CPG is described by following equations:

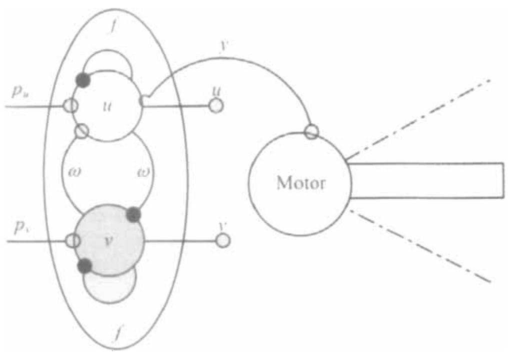


Fig. 4 Segmental CPG based on Zhang oscillator.

$$\begin{cases} \dot{u}=\omega v + k\left(-\dfrac{u}{r}+\dfrac{4}{\pi}\tan^{-1}\left(\dfrac{u}{r}\right)\right)+p_u(t) \\ \dot{v}=-\omega u+k\left(-\dfrac{v}{r}+\dfrac{4}{\pi}\tan^{-1}\left(\dfrac{v}{r}\right)\right)+p_v(t) \end{cases} \tag{7}$$

$$y=u\ ,$$

where p_u, p_v denote the external inputs composed of descending commands and sensor feedback, y denotes the output from the inhibitory neuron to the motor.

3.3 Bionic neural network for fish-robot locomotion

The neural network of CPGs are often modelled as a chain of coupled nonlinear neural oscillators[22]. We also proposed a bionic neural network composed of one chain of many CPGs based on Zhang oscillator as shown in Fig. 5. The descending commands from the high level controller include body swing angular frequency, amplitude and bias angle for turning. The number of artificial CPG controllers is corresponding to the joints which are driven by motor equipments.

The intersegmental connection strength and time delay in swimming may be modelled by two coupled parameters which are defined as below:

$$\begin{cases} s_b = s\delta(t-\Delta T),\ s_f = 0 & \text{forward} \\ s_b = 0,\ s_f = s\delta(t-\Delta T) & \text{backward} \end{cases}, \tag{8}$$

where s denotes the coefficient of intersegmental connections, ΔT is the average time delay in the intersegmental connections.

We assume that the number of waveform presented in the body is n_λ, and approximately holding up in despite of undulatory frequency and swimming speed changing. The equation to calculate the time delay is given as

$$\Delta T=\frac{n_\lambda}{nf}=\frac{2\pi n_\lambda}{n\omega}, \tag{9}$$

where n is the number of joints, f is the undulatory frequency (Hz) .

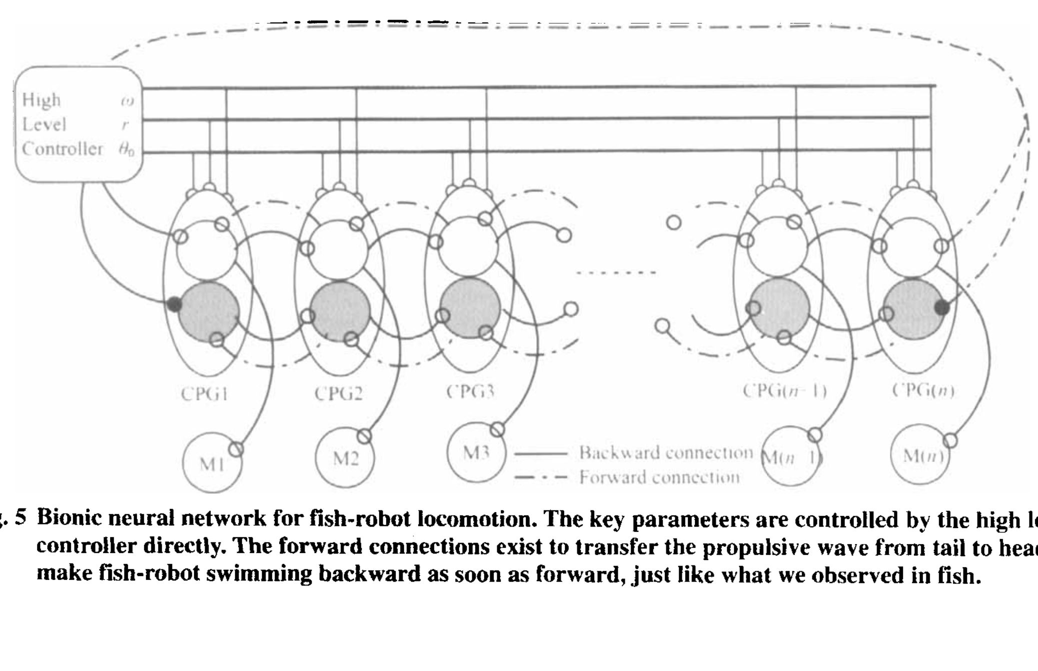


Fig. 5 Bionic neural network for fish-robot locomotion. The key parameters are controlled by the high level controller directly. The forward connections exist to transfer the propulsive wave from tail to head to make fish-robot swimming backward as soon as forward, just like what we observed in fish.

The bionic neural network may be divided into three sections, the head segment, tail segment and middle segments. The dynamics of head segment is described by the following equations:

$$\begin{cases} \dot{u}_1 = \omega v_1 + f(u_1,k,r) + s_f u_2 + s_b p_u(t) \\ \dot{v}_1 = -\omega u_1 + f(v_1,k,r) + s_f v_2 + s_b p_v(t) \end{cases}. \tag{10}$$

The dynamics of middle segments has a uniform expression which is described as

$$\begin{cases} \dot{u}_i = \omega v_i + f(u_i,k,r) + s_b u_{i-1} + s_f u_{i+1} \\ \dot{v}_i = -\omega u_i + f(v_i,k,r) + s_b u_{i-1} + s_f v_{i+1} \end{cases}, \tag{11}$$

$$i = 2,3,\cdots,n-1.$$

The dynamics of tail segment is described by the following equations:

$$\begin{cases} \dot{u}_n = \omega v_n + f(u_n,k,r) + s_b u_{n-1} + s_f p_u(t) \\ \dot{v}_n = -\omega u_n + f(v_n,k,r) + s_b v_{n-1} + s_f p_v(t) \end{cases}. \tag{12}$$

3.4 Modelling of fish-robot

There are many fish-robots developed for different purpose in recent years[11]. We classify them by the mechanical characters into following three modes.

(a) Anguilliform fish-robots. They consist of many joints from head to tail. A traveling wave is transferred from the head to tail when they are swimming in the water. The simulation model of anguilliform fish-robot is shown in Fig. 6(a).

(b) BCF fish-robots. They consist of several joints from the body to tail. When they are swimming in the water, the head almost keeps still, but the latter body and tail fin present an increscent traveling wave. The simulation model of the BCF fish-robot is illustrated in Fig. 6 (b).

(c) Undulatory fin fish-robots. They are composed of several undulatory fins and rigid column body. Each undulatory fin consists of a thin membrane and many fin rays which are mounted in parallel on the rigid body and individually driven by one actuator. The model of undulatory fin fish-robot is shown in Fig. 6(c).

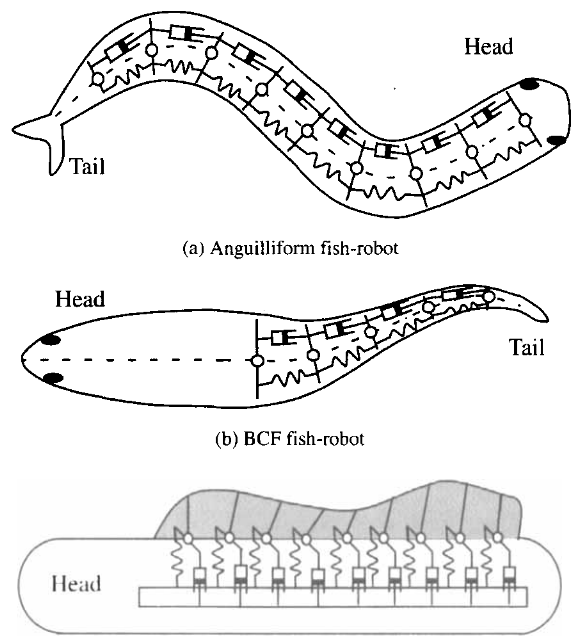
The anguilliform and BCF fish-robots have turning ability, but the undulatory fin fish-robot which is only driven by one undulatory fin can not turn at all. The main differences among them are number of joints, intersegmental coupling strength and swing frequency.

We assume that each joint of fish-robots is driven by one actuator with one turning freedom. The dynamics of the joint is given as

$$J\ddot{\theta} + D\dot{\theta} + k_s\theta = \tau, \tag{13}$$

where θ is the joint angle, $\dot{\theta}$ is the angular velocity, $\ddot{\theta}$ is the angular acceleration, J is the rotating inertia, D is the damping coefficient, k_s is the restore force and τ is the driving moment of the actuator.

The robot joints are often connected with other joints or impacting with surroundings. So the parameters of joint dynamics are not holding up but changing all time. They are almost impossible to be measured quite accurately or modelled with exact mathematic dynamic functions. But time average values of the parameters can be adopted for the distinct periodicity of the fish-robot movements.



(a) Anguilliform fish-robot

(b) BCF fish-robot

(c) Undulatory fin fish-robot

Fig. 6 Different fish-robots.

4 Simulation results

4.1 Simulation model

The complex dynamics of synchronization and control of chaos in a system of strongly connected Wilson-Cowan neural oscillators was investigated by Ueta[19]. The system composed of the bionic neural network and rigid dynamics modules has more *complex* dynamic properties and is difficult to be analyzed in linear or nonlinear control theory. We constructed experiments fully based on Matlab Simulink environment for its accuracy, visual ability and conveniency.

We restrict our focus on the control methods of the fish-robot swimming locomotion such as startup, stop, forward or backward swimming and turning. All the parameters in the bionic network can be individually and manually set. We use a uniform model to simulate the different modes of fish-robots by modulating a few parameters, just like the similar principles of neural networks in different modes of fishes. The dynamic equations of each CPG module are given by Eqs. (7) – (12). The output of each CPG module in Eq. (7) is connected to a segmental controller which controls the corresponding joint by Eq. (13).

A simple proportional controller is adopted to emulate the properties of servo-motor which is widely used in fish-robots. The driving force is given as

$$\begin{aligned} \tau_i &= K_P\left(\theta_{\text{out}\_i} - \theta_{\text{in}\_i}\right) \\ \theta_{\text{in}\_i} &= u_i + \theta_{\text{turn}} \end{aligned} , \qquad (14)$$

where θ_{in_i} denotes the object angle of the i-th joint and is determined by the segmental CPG output u_i, θ_{out_i} denotes the i-th joint angle which can be measured by potentiometer or encoder quite accurately, θ_{turn} means the turning weight inflicted on each joint from the high level controller and K_P is the proportional gain.

4.2 Startup or stop of swimming

We set the system parameters of initial condition as below:

(1) $\theta_{\text{turn}} = 0$, $n=17$, $n_\lambda = 1$

(2) $\omega = 4\pi$, $k = 2$, $r = 5^\circ$

(3) $u_i = 0$, $v_i = 0$ $i=1,2,\cdots,n$

(4) $s_h = \delta(t - \Delta T)$, $s_t = 0$

(5) $p_u(t) = 10\left(\text{step}(t-0.1) - \text{step}(t-0.11)\right)$

$p_v(t) = 0$

(6) $K_p = 10$, $J = 0.05$, $D = 0.1$, $k_s = 1$ (15)

where step$(t - t_0)$ denotes the normal step function starting at t_0, $p_u(t)$ and $p_v(t)$ denote the startup function of swimming. Fig. 7(a) shows the change of the network outputs in $t \in [0,2]$. The network has been activated in turn from CPG1 to CPG6 and comes into steady oscillation with constant pulse delay (or time delay). Fig. 7(b) shows the change of joint angle in the same process. A whole startup process of fish-robot body is illustrated in Fig. 8 in the time range of [0, 3.5]. The oscillation is transferred from the head to tail in several periods.

The limit cycles' radius of bionic network oscillation is mainly determined by the system parameter r, and it can not be zero which causes "divided by zero" computing error in dynamic update calculation. We continuously reduce its absolute value until very small but not zero to decrease the undulatory amplitude. If the swing amplitude of fish-robot body is quite small and can not be observed with human eyes, we say that "the swimming is stop". This method is accord with the principle of animal's basal ganglion inhibitory control of the rhythmic movements.

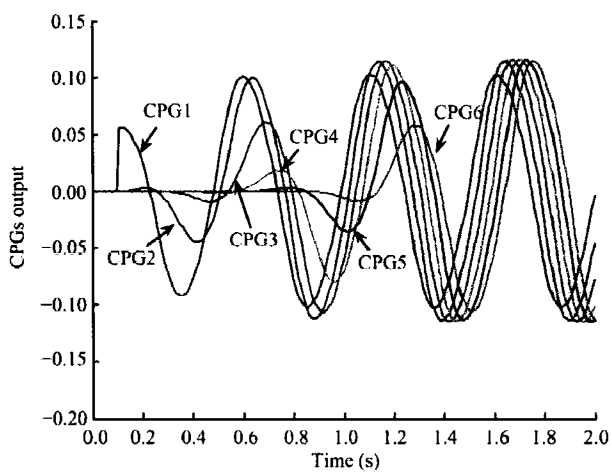


Fig. 7(a) CPGs outputs in the starting.

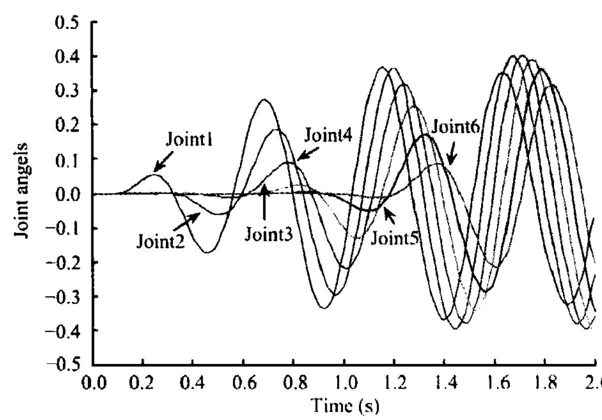


Fig. 7(b) Joint angles in the startup.

The stop function is described as

$$r(t) = r_0\left(1 - \frac{2}{\pi}\tan^{-1}\left(k_r \int_{t=0} \mathrm{step}(t - t_s)\right)\right), \quad (16)$$

where r_0 is the steady swimming parameter, t_s is the beginning time of stop process, k_r denotes the decrease speed. Fig. 9 shows the whole stop process of swimming with $t_s = 6$ s, $k_r = 5$.

4.3 Forward and backward swimming

The system parameters to sustain steady forward swimming are set in Eq. (15). Fig. 10 shows the change of fish-robot body in steady forward swimming with time interval dT = T/4. The swimming amplitude and frequency are mainly determined by r and ω, respectively.

The backward swimming can be easily achieved by only exchanging the values of s_f and s_b, in other words, turn the direction switch from the forward to backward. The change of fish-robot body in backward swimming with time interval dT = T/4 is illustrated in Fig. 11.

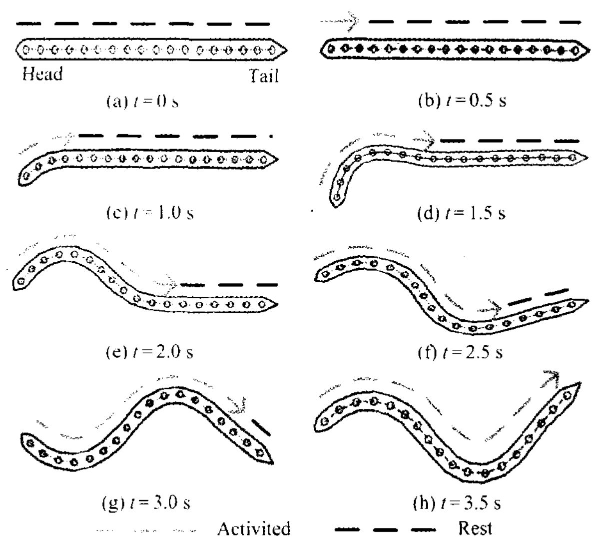


Fig. 8 Startup of swimming.

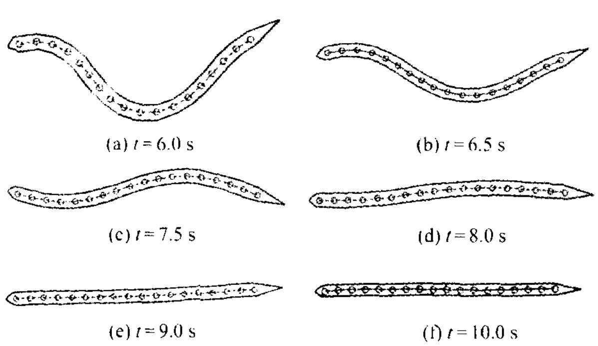


Fig. 9 Stop of swimming.

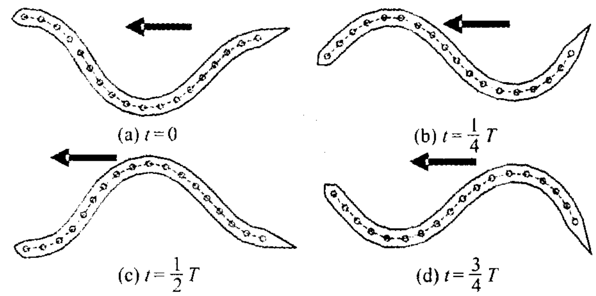


Fig. 10 Forward swimming.

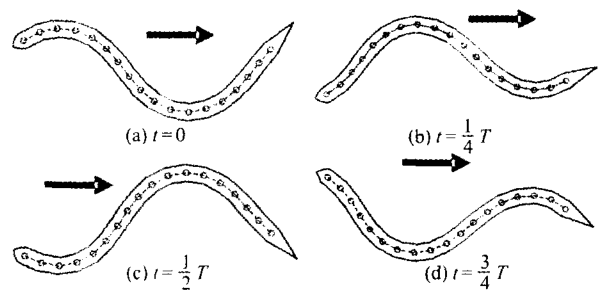


Fig. 11 Backward swimming.

4.4 Turning

The fish can turn to right or left by contracting the corresponding side muscles. We use the same principle in fish-robot turning process. Fig. 12 shows the change of fish-robot body in a turning right period with the turning strength θ_{turn}=5°. The change of fish-robot body has contrary process in a turning left period with the turning strength θ_{turn}= −5°. The turning direction is determined by the sign of turning strength, and the turning speed is continuously modulated according to the value of turning strength.

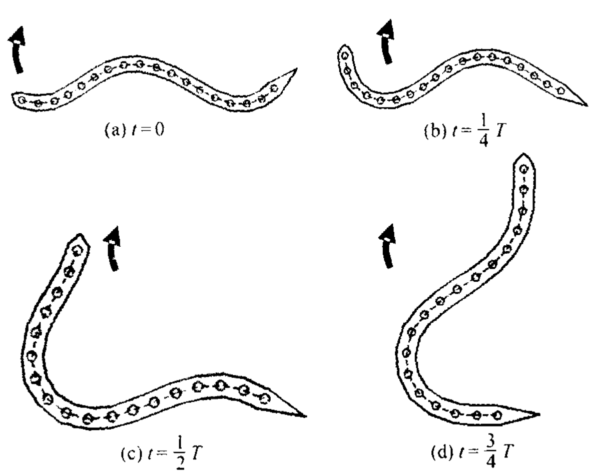


Fig. 12 Turning right.

5 Conclusion

In this paper, we proposed a bionic neural network which controls fish-robot swimming. The bionic neural network consists of a high level controller and one chain of CPGs. Each CPG contains a nonlinear neural Zhang oscillator which shows similar properties of sine-cosine model. We modeled the dynamics of all fish-robot joints into a 2-degree uniform and used them in the simulation. It presents high performance in controlling the fish-robot to execute various motions such as startup, stop, forward swimming, backward swimming and turn. The bionic neural network can be adopted in the design of high performance control system for future fish-like robots. It can also be used in other bionic robots with slight modification for its successful imitation of animal central nervous system.

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