Particle Swarm Optimization-based Central Patter Generator for Robotic Fish Locomotion

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***Abstract*—This paper proposes particle swarm optimization-based central pattern generator (CPG) to generate rhythmic signals for fish-like locomotion of robotic fish. The robotic fish's wave form approximates fish's traveling wave. Since each joint angle of the robotic fish is modeled by a periodic function, it can be easily produced by a CPG. A CPG consists of biological neural oscillators, which can produce coordinated rhythmic signals by using simple input signals. The proposed CPG uses a neural oscillator for each joint of a robotic fish. To optimize the parameters of the CPG which determine the output signals, particle swam optimization (PSO) is employed. The effectiveness of the proposed CPG is demonstrated by computer simulation and real experiment with the robotic fish Fibo, developed in the Robot Intelligence Technology Lab., KAIST.**

I. Introduction

Nowadays, a lot of researches in robotics have been inspired by natural phenomena. Since animals such as birds and fishes evolved for a long time, they have efficient characteristics which is well optimized through evolution. Those characteristics are usually adopted as the key mechanisms to build robots. To construct a robotic fish which moves efficiently and faster underwater, mimicking real fishes' locomotion has been researched and it is known that locomotion of real fish has higher efficiency compared to propeller-driven underwater vehicle [1].

Previous researches on robotic fish focus on the propulsion mechanism and mimicking locomotion of real fish [2]-[6]. It is very complicated to build a mathematical model because of complexity of hydrodynamics and kinematics of swimming of fish and stream of water. Since actuators consume much energy to generate propulsion in the water because of resistance force of water, robotic fish using artificial muscle were developed [7], [8]. Pectoral fins and dorsal fin also help increase the efficiency of locomotion and many researchers studied about those issues [9], [10]. Various fish swimming modes provide precise movements and applications of robot fish were suggested for playing robot water polo and displaying in aquarium, etc. [11], [12].

One approach to generate fish-like locomotion is to build a model from the real fish's locomotion, which is described as traveling wave forms. This approach concentrates on mimicking the traveling wave by changing the shape of robotic fish's body. However, this approach needs a large memory space to store every trajectory of each joint angle.

The other approach is to use a biologically-inspired oscillating signal generator such as central pattern generator (CPG) [13]-[16]. The CPG consists of biological neural oscillators and generates various multidimensional rhythmic signals. The locomotion of animals uses this type of locomotion process. Since parameters of the CPG are given arbitrarily and experimentally, the locomotion of robotic fish is different from that of real fish and the merits of fish-like swimming are hardly expected.

In this paper, a CPG of which parameters are optimized to follow traveling wave is proposed for fish-like locomotion. Particle swarm optimization (PSO) [17], a robust stochastic evolutionary computation technique based on the movement and intelligence of swarms, is used in order to optimize the parameters of the proposed CPG structure. The effectiveness of the proposed CPG is demonstrated by computer simulation and real experiment with the robotic fish "Fibo," developed in the Robot Intelligence Technology Lab., KAIST in 2010.

The remainder of this paper is organized as follows. Section II introduces preliminaries on CPG and PSO. Section III describes the swimming pattern model for robotic fish and proposes a CPG structure. Section IV defines the optimization problem for the proposed CPG structure. The optimized results utilizing computer simulation and real experiment with Fibo are shown in Section V. Finally, conclusions and future works follow in Section VI.

II. Preliminaries

A. Central Pattern Generator

The neural oscillator model for central pattern generator is biologically inspired to generate a rhythmic signal. Each neuron of the neural oscillator in Fig. 1 is defined as follows [18], [19]:

$$\tau_r \dot{u}_i + u_i = -\sum_{j=1}^{N} w_{ij} y_j - \beta v_i + u_0 + Feed_i, \quad (1)$$

$$\tau_a \dot{v}_i + v_i = y_i, \quad (2)$$

$$y_i = max(0, u_i), \quad (3)$$

where u_i is the inner state, v_i is the self-inhibition state, y_i is the output signal of the ith neuron and u_0 is the external input signal. w_{ij} is the connecting weight between the ith and jth neurons, τ_r and τ_a are time constants, β is the weight of the

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self-inhibition and $Feed_i$ is the feedback signal from sensors of the robot. β, u_0, τ_r, τ_a and w_{ij} are constant parameters. τ_r and τ_a have influence on the shape and frequency of output signal and w_{ij} determines phase difference between the ith and jth neurons. The output amplitude is determined by u_0.

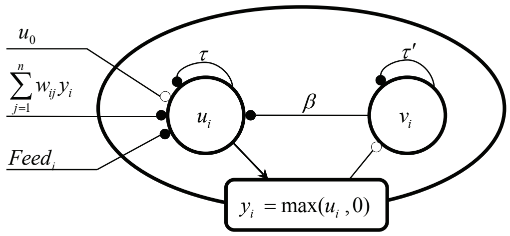

Fig. 1. Neuron of neural oscillator.

The neural oscillator is generally composed of one or more neurons which are connected to each other with connecting weight, w_{ij}. Therefore, the identical number of wave signals with that of neural oscillators are generated to control actuators. This structure is generally called CPG structure.

B. Particle Swarm Algorithm

In this paper, PSO is employed to optimize parameters of CPG. In PSO, each particle has its position and velocity vectors. They are attracted stochastically toward the better positions considering their personal best position and their neighbors' best position.

Overall pseudo code of Standard PSO is described in [17]. A population is a set of N particles. At first, the velocity $\mathbf{v}_i$ and the position $\mathbf{x}_i$ of each particle in the population is randomly initialized on D-dimensional space. At each iteration, each particle evaluates the fitness and updates the personal best position $\mathbf{x}_i^p$. The global best position $\mathbf{x}^g$ is set to the position of the particle which has the maximum fitness. After the evaluation phase, each particle updates its position and velocity as follows:

$$\begin{cases} \mathbf{v}_i = & w \cdot \mathbf{v}_i + c_p \cdot \phi_1(\mathbf{x}_i^p - \mathbf{x}_i) + c_g \cdot \phi_2(\mathbf{x}^g - \mathbf{x}_i), \\ \mathbf{x}_i = & \mathbf{x}_i + \mathbf{v}_i, \end{cases} \tag{4}$$

where w, c_p and c_g are constants, and ϕ_1 and ϕ_2 are independent random real values uniformly distributed in $[0, 1]$. $\mathbf{v}_i$ and $\mathbf{x}_i$ represent the velocity and position of the p_i, respectively. Random values ϕ_1 and ϕ_2 are generated for each particle, for each iteration. After the position and velocity update process, the algorithm goes back to the evaluation process and starts over again. The algorithm terminates when a termination criterion is met.

In the experiments, an improved version of PSO were used [20], [21]. The improved version of PSO uses the neighbor topology instead of the global topology. Neighborhood links are implemented with an $N \times N$ binary matrix and randomly initialized. Each element of the link matrix is set to 1 or 0 with a certain probability. The global best terms of (4) are replaced with the neighbor best terms, which are obtained from the linked neighbors. The neighborhood links are re-initialized when the best fitness value of the population is improved compared to the previous iteration.

III. CPG-BASED CONTROL STRUCTURE

A. Robotic-fish Swimming Pattern Model

It is very difficult to construct a precise mathematical model of real fish's periodic locomotion analytically since its locomotion involves hydrodynamics and kinematics. Therefore, kinematical model which was originally suggested by Lighthill has been widely used [22]. The traveling wave equation is as follows:

$$y_{body}(x,t) = (c_1 x + c_2 x^2) sin(kx - wt), \tag{5}$$

where y_{body} is the transverse displacement of body, x-axis is the center line of the undulation wave, x is the displacement along the center line. k is the body wave number with $k = 2\pi/\lambda$, where λ is the wave length. c_1 and c_2 are the linear and quadratic wave amplitude envelope, respectively. w is the body wave frequency ($w = 2\pi f = 2\pi/T$) and t is the time.

To generate fish-like locomotion, the body motion of robotic fish should continuously track the traveling wave forms with respect to time as shown in Fig. 2.

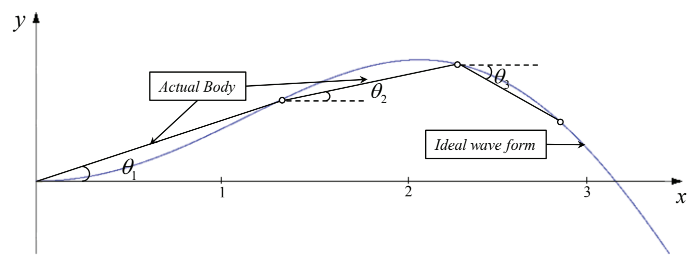

Fig. 2. Traveling wave at a certain time and the connected fish links.

The robotic fish is composed of a couple of connected links. As the numbers of joints and links increase, its motion trajectory becomes more similar to the traveling wave forms. However, this increases the number of actuators, which decreases energy efficiency and the control of joints becomes more complicated. Therefore, 2-4 connected links are commonly used for modeling a fish of Carangiform. Since each link is a rigid body, wave form approximation is needed to track a traveling wave. Online calculation of the joint angles which minimizes the difference between the traveling wave and the trajectory of the flapping links takes a long time. It is often impossible to perform in real time.

In many previous researches, the joint angles are pre-calculated and are saved to a lookup table in advance. While this can help generate locomotion of the robotic fish in real time, a large amount of memory space is needed to save all the trajectory data for various speeds and amplitudes. Another approach to generate control inputs is approximating the trajectory of each joint to a sinusoidal function. It does not need as much space as pre-calculating approach and the traveling wave frequency can be changed freely, but it is hard to change the swimming mode such as cruising, turning smoothly, etc.

B. Design of CPG Controller for Robotic Fish

Since joint angles oscillate with the same period, CPG, which is composed of several interconnected neurons, can be used for generating the joint angle trajectories. CPG has a small number of variables and the calculation for deriving joint angles can be performed in real time. Therefore, in this paper, the CPG structure is employed to generate the robotic fish locomotion.

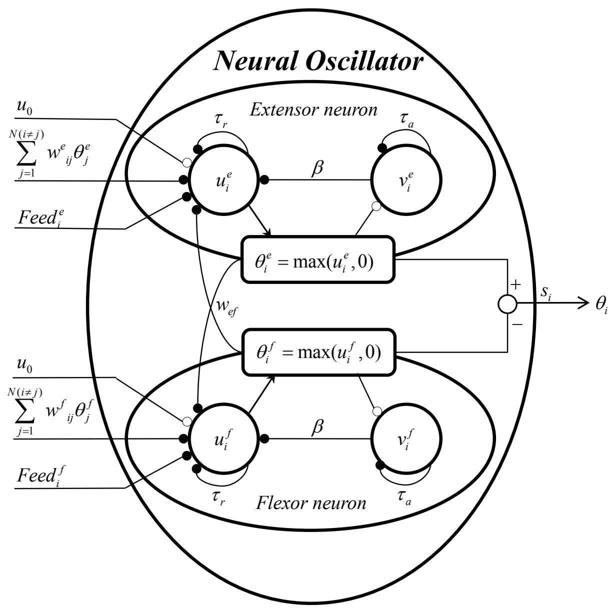

Fig. 3. Neural oscillator structure.

In the proposed structure, the basic rhythmic locomotion is assumed to be generated by neural oscillators each of which consists of two mutually excited neurons; an extensor neuron and a flexor neuron, with self-inhibition effect, which are linked reciprocally via inhibitory connections. Each neuron is connected with the same type of neurons in other neural oscillators as shown in Fig. 3. By the effect of this relationship, rhythmic signals are generated. The relationship is represented by the following nonlinear differential equations:

$$\tau_r \dot{u}_i^e + u_i^e = -w_{ef} y_i^f - \sum_{j=1}^{3(j\neq i)} w_{ij}^e y_j^e - \beta v_i^e \quad (6)$$

$$+u_0 + Feed_i^e, \quad (7)$$

$$\tau_a \dot{v}_i^e + v_i^e = y_i^e, \quad (8)$$

$$y_i^e = max(0, u_i^e), \quad (9)$$

$$\tau_r \dot{u}_i^f + u_i^f = -w_{ef} y_i^e - \sum_{j=1}^{3(j\neq i)} w_{ij}^f y_j^f - \beta v_i^f \quad (10)$$

$$+u_0 + Feed_i^f, \quad (11)$$

$$\tau_a \dot{v}_i^f + v_i^f = y_i^f, \quad (12)$$

$$y_i^f = max(0, u_i^f), \quad (13)$$

$$\theta_i = s_i(y_i^f - y_i^e), \quad (14)$$

where i denotes the ith neural oscillator (NO) and the superscripts e and f denote the extensor neuron (E) and the flexor neuron (F), respectively. s_i is the amplitude scaling factor to normalize joint angle's input signal and w_{ef} is the connecting weight between the extensor neuron and the flexor neuron. θ_i is the angle of the ith joint in the robotic fish. Meanings of other variables are the same as described in Section II-A. The proposed CPG structure for a robotic fish with three links is shown in Fig. 4. It generates oscillating signals each of which controls the corresponding joint.

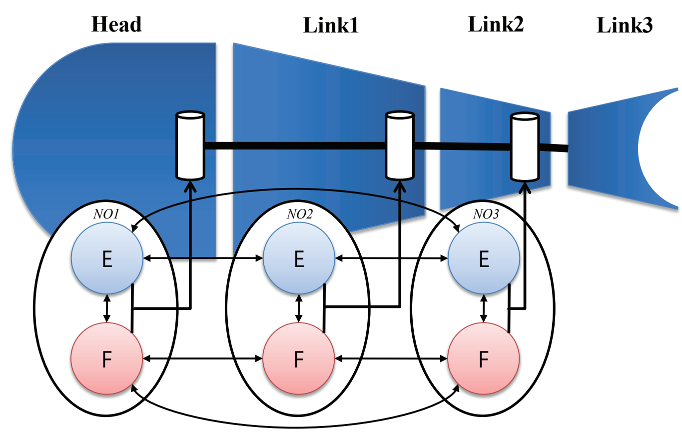

Fig. 4. CPG structure of the robotic fish with tree joints.

However, it is not easy to choose parameters heuristically to obtain signals which follow the traveling wave. Therefore, PSO is employed to optimize the parameters to obtain the desired signals.

IV. CPG Parameter Optimization

The proposed CPG structure has 26 parameters which consist of the weight of the self-inhibition, the external input signal, the amplitude scaling factors, the connecting weights and the time constants. The external input signal can be arbitrarily determined from the experiment because they do not significantly affect the features of output signals. On the other hand, the remaining 19 parameters should be properly determined to generate desired output signals. In previous researches, these parameters were determined experimentally. However, it is hard to set these parameters for the link flapping motion which closely tracks the desired traveling wave.

In this paper, these parameters are optimized by PSO. Parameters to be optimized are time constants τ_r and τ_a which decide the body wave frequency w in (5), and amplitude scaling factors s_i, welf-inhibition weight β, and connecting weights w_{ef}, w_{ij}^e, w_{ij}^f which are related to the shape of the generated signals. The optimization procedure is performed with the CPG structure which has three neural oscillators as shown in Fig. 4.

The objective function for PSO is defined by integrating the difference from 0 sec to T sec as follows:

$$f_w = \int_0^T |e(t)|dt \tag{15}$$

with

$$\begin{aligned}
e(t) &= \sum_{i=1}^{3} \int_{x_{i-1}(t)}^{x_i(t)} |y_{body}(x,t) - y_{link_i}(x,t)|dx, \\
y_{body}(x,t) &= (c_1 x + c_2 x^2) sin(kx - wt), \\
y_{link_i}(x,t) &= \tan(\theta_i(t))(x - x_i(t)) + y_i(t)), \\
x_i(t) &= x_{i-1}(t) + l_i \cos(\theta_i(t)), \\
y_i(t) &= y_{i-1}(t) + l_i \sin(\theta_i(t)), \\
x_0(t) &= 0, \\
y_0(t) &= 0,
\end{aligned}$$

$$i = \begin{cases} 1 & \text{if } x_0 \le x < x_1, \\ 2 & \text{if } x_1 \le x < x_2, \\ 3 & \text{if } x_2 \le x \le x_3, \end{cases}$$

where f_w is the objective function for the connecting weights and the amplitude scaling factors in a certain period T, $e(t)$ is the difference between the desired traveling wave and the link flapping wave forms of the robotic fish at time t, $y_{body}(x,t)$ is the function of the desired traveling wave, i denotes the ith link, $y_{link_i}(x,t)$ is the function of the ith link, $x_i(t)$ is the x-coordinate of the starting point for the ith link at time t, $y_i(t)$ is the y-coordinate of the starting point for the ith link of flapping part at time t, and $x_0(t)$ and $y_0(t)$ denote the xy-coordinate of the starting point for the first in flapping part. Parameters obtained by this process are set in the CPG structure, and then output signals are continuously generated to control the joints.

V. Exprimental Results

Effectiveness of the proposed algorithm was demonstrated with computer simulations and a robotic fish “Fibo.” The proposed CPG structure was configured to have three neural oscillators. In the structure, among 26 parameters, 19 parameters were optimized for fish-like locomotion of Fibo.

A. Fibo

Fibo was developed in the RIT lab., KAIST in 2010. It has four links connected by three joints as shown in Fig. 5. Fibo is categorized into carangiform using oscillating wing [23], [24].

Fibo has a camera to locate its position from the captured images, and three ultrasonic sensors in the head to detect obstacles. An artificial air bladder which is composed of a small ballast tank and a center of gravity controller is used to submerge. It also has a low frequency RF module for underwater communication.

The latest version of Fibo is Fibo3, which was designed based on the shape of a prehistoric fish, Dunkleosteus terrelli. Fib. 6 shows the sideview of Fibo3. Its length is 1.2 meter including the caudal fin and its weight is 20.0 kg. The proposed CPG structure was used to control the actuators of Fibo for fish-like swimming.

B. Parameter Optimization

The desired traveling wave was set with $c_1 = 0.08$, $c_2 = 0.0$, $k = 1.0$, $w = \pi$, which were choosen arbitrarily in order to set the wavelength and the period of locomotion to 2π and 2.0, respectively. After setting the traveling wave equation, CPG parameters such as τ_r, τ_a, s_i and w_{ij} were optimized to track the traveling wave using the optimization procedure which is described in Section IV. Fig. 7 shows the smallest objective function value along generations of the best result among 50 trials. The average value of the optimized objective function values was 0.83254. The objective function values were calculated for two periods, i.e. 4.0 seconds, after 50.0 seconds for stabilizing the output signals generated from the CPG structure. The CPG parameters obtained from the optimization by PSO are shown in Table I.

TABLE I
Optimized Parameters.

τ_r	2.99985	τ_a	0.429918
w_{ef}	3.02762	β	9.84874
w^e_{12}	3.45688	w^f_{12}	5.8351
w^e_{13}	3.83181	w^f_{13}	7.7661
w^e_{21}	5.3505	w^f_{21}	2.80495
w^e_{23}	6.55237	w^f_{23}	3.11608
w^e_{31}	5.19203	w^f_{31}	4.93922
w^e_{32}	3.58118	w^f_{32}	2.53456
s_1	0.645567	s_2	2.73989
s_3	2.3313		

C. Simulation and Fibo Experiments

The output signals generated from neural oscillators with the optimized parameters are shown in Fig. 8. Fig. 9 shows the swimming body motion using the signals, which confirms that flapping link wave forms of the robotic fish tracked the traveling wave forms. Fibo controlled by the proposed CPG with the PSO optimized parameters is shown in Fig. 10

To swim with various speeds for different types of locomotion, PSO should be applied to provide proper CPG parameters for each type of locomotion. These parameter values should be saved in advance. Saving these parameters requires much less memory space than saving trajectories of all actuators. Also, the proposed structure can generate more fish-like locomotion than the existing CPG structures of which parameters were set experimentally.

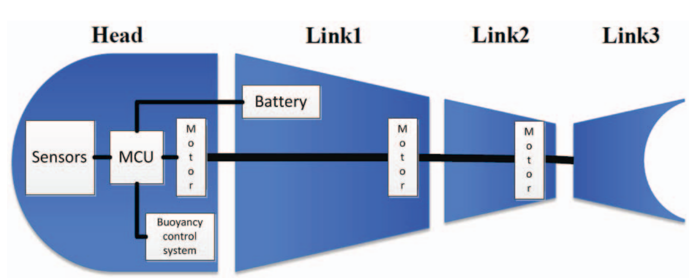

Fig. 5. The components of Fibo

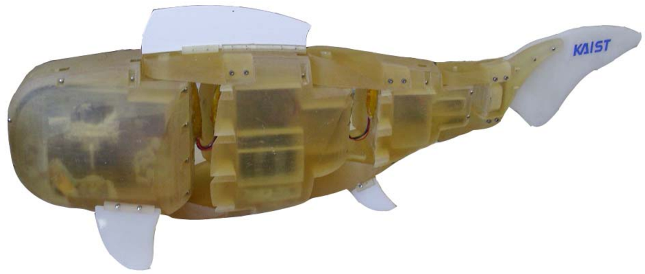

Fig. 6. Fibo3

VI. Conclusion and Further works

This paper proposed a locomotion generator for the robotic fish using the central pattern generator (CPG). The CPG structure of neural oscillators was developed to generate coordinated rhythmic signals and particle swarm optimization (PSO) was employed to optimize the parameters of the CPG structure. The proposed CPG structure controlled the swimming body of a robotic fish by generating joint angles. As a result, the link shape of the swimming body tracked the desired traveling wave to swim fish-like. In order to demonstrate the performance of the proposed CPG structure which was optimized by PSO, computer simulations were carried out and experimented with the robotic fish, Fibo, which was deveoped in the Robot Intelligence Technology lab., KAIST in 2010. As a further work, researches will be focused on providing feedback signals obtained from sensors to the CPG to generate signals for various types of swimming.

VII. Acknowledgments

This work was supported (National Robotics Research Center for Robot Intelligence Technology, KAIST) by Ministry of Knowledge Economy under Human Resources Development Program for Convergence Robot Specialists.

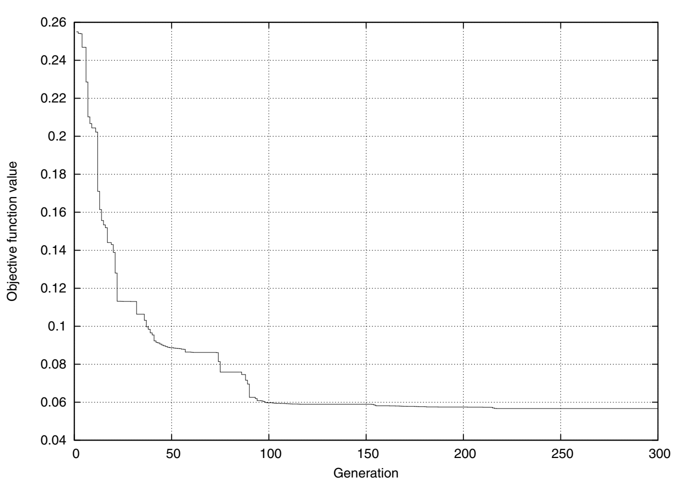

Fig. 7. Objective function value.

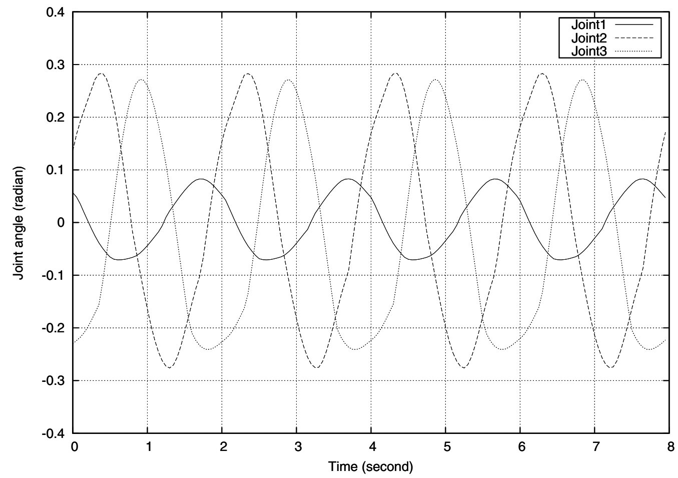

Fig. 8. The output signals of joints.

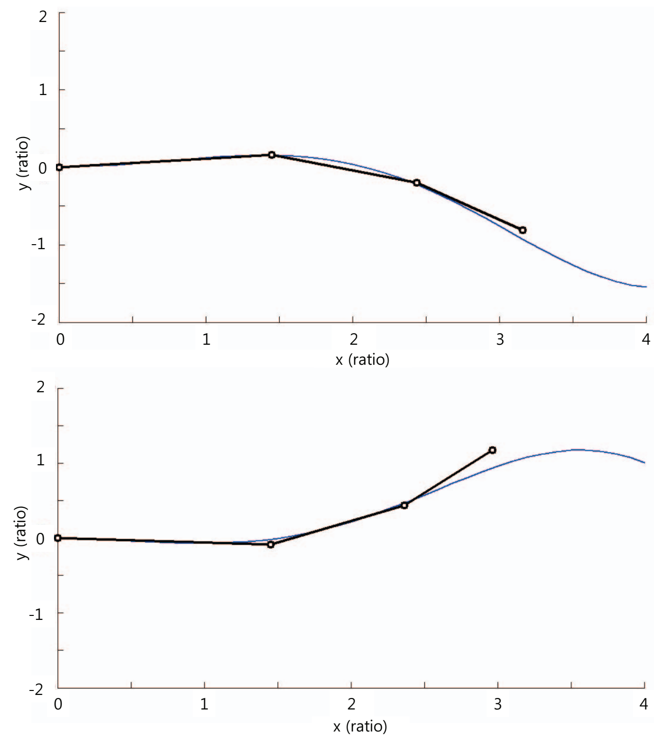

Fig. 9. Traveling wave and the shape of the swimming part at t = 0.0 s, t = 0.5 s, t = 1.0 s, t = 2.0 s (from top to bottom)

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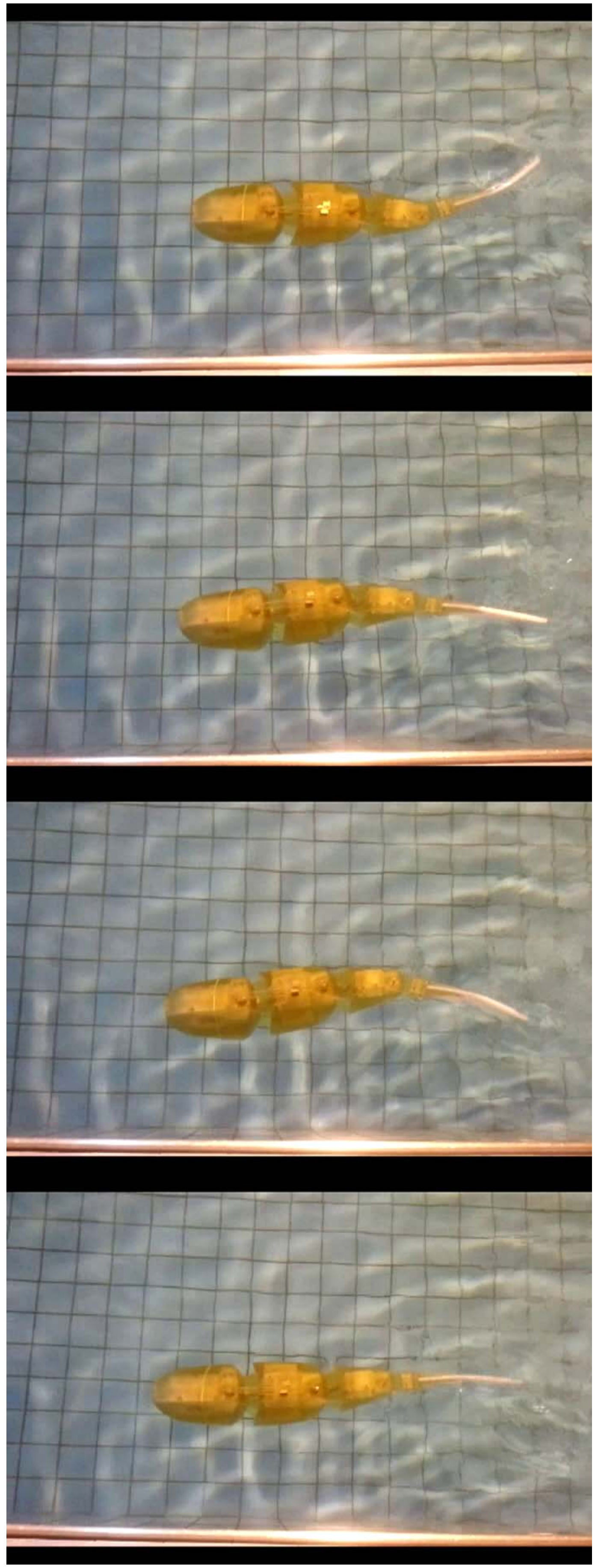

Fig. 10. Fibo controlled by the proposed structure.