TRACKING CONTROL FOR A BIOMIMETIC ROBOTIC FISH GUIDED BY ACTIVE VISION

Feihu Sun,* Junzhi Yu,* Peng Zhao,* and De Xu**

Abstract

This paper is concerned with control issue of active vision guided tracking for an agile robotic fish. A control method for guaranteeing the stability of the swinging head is proposed, which aims at steady image data acquisition. Then, a control framework with the properties of multiple stages is presented. The artificial landmark-based visual positioning and directional control implemented as a fuzzy logic controller are combined in this framework. Furthermore, reasonable control strategies are put forward to balance the kinematic performance and the tracking accuracy. Finally, tracking tests have been conducted on the autonomous robotic fish merely guided by embedded vision. The experimental results indicate the feasibility and reliability of the proposed methods.

Key Words

Tracking control, active vision, stability control, biomimetic robotic fish

1. Introduction

The ocean has immense space, tremendous species of creatures and rich energy resources, which makes it inevitable so that the ocean will be further explored for sustainable development. However, more than 95% of the ocean still remains to be explored and developed [1]. Autonomous underwater vehicles (AUVs) and remotely operated vehicles, effective equipment to exploit unknown oceans, have drawn great attention.

With visual systems mounted, underwater robots can perceive more about aquatic environments, which contributes to widening application range of the underwater robots. Station keeping, video mosaicking, feature tracking, intervention-class AUVs, and navigation and positioning compose a variety of applications of vision-guided AUVs [2]. In general, visual measurement and control are employed for complex tasks in AUVs. Fundamentally, image preprocessing and processing are carried out for feature extraction. An algorithm of image enhancement by using empirical mode decomposition was put forward to obtain accurate features [3]; Eustice *et al.* proposed a scheme of underwater navigation based on simultaneous localization and mapping (SLAM) [4]. In addition, after features are acquired, visual control models involving position-based servo control and image-based servo control can be designed. Gracias *et al.* proposed an image-based servo control strategy for autonomous navigation of underwater robots [5]; Autonomous grasping using position-based visual servos was studied in a multi-purpose intervention AUV (I-AUV) [6].

The biomimetic robotic fish with embedded visual systems is an excellent paradigm of AUVs. Compared with traditional propellers, fins have evolved excellent propulsion capabilities, including smaller noise and higher efficiency. Meanwhile, using visual information as a clue, an embedded vision-based robotic fish can perceive more about aquatic environments. As a result, it is feasible to accommodate the fish to the complex environments and implement corresponding motion control. Recently, researchers are paying close attention to active vision in robotic fishes. For instance, Yu *et al.* investigated active tracking of a colour patch in a robotic fish guided by visual information [7]; Takada *et al.* designed a robotic fish with a single joint, which was used to predict target positions via visual features [8]; Hu *et al.* proposed an improved CAMSHIFT algorithm to implement visual tracking [9], [10]. However, this research is still primary and confronted with great challenges. That is because that illumination in aquatic environments and agility of the robotic fish obstruct steady image data acquisition and the embedded systems have limited capacities.

On the basis of previous research on fish-like swimming [7], [11]–[14], embedded vision based tracking control for a self-propelled robotic fish is proposed to integrate agile locomotion with control accuracy. Firstly, a stability control method to enhance the stability of the head is proposed. Note that this stability control is just able to minimize the swing of the head rather than absolutely eliminate the swing. Moreover, a directional control

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scheme with visual inputs is constructed, which divides the image-based servo control into directional control with multiple stages. Reasonable control strategies are subsequently proposed to strike a compromise between flexibility and control accuracy.

2. System Design of the Biomimetic Robotic Fish

The mechanical configuration of the biomimetic robotic fish with embedded vision is shown in Fig. 1. Efficient and agile locomotion and precise control are predominantly attributed to the elaborate mechanism. Specifically, a rigid head is fabricated with a transparent window, where a CMOS camera (OV2655, 30 fps) is mounted for image acquisition. A flexible soft body with four joints and a crescent caudal fin provide the robotic fish with most of thrust forces [15], which generate forward and yawing swimming. In addition, a pair of independent pectoral fins is introduced to generate pitching angles and the complementary thrust forces. The mechanical parameters of the biomimetic robotic fish with embedded vision are tabulated in Table 1. Note that the well-fabricated and equipped robotic fish can suspend in aquatic environments, guaranteeing balance between the gravity and the buoyancy. In practice, the centre of the gravity is lower than that of the buoyancy, which avoids rolling without control.

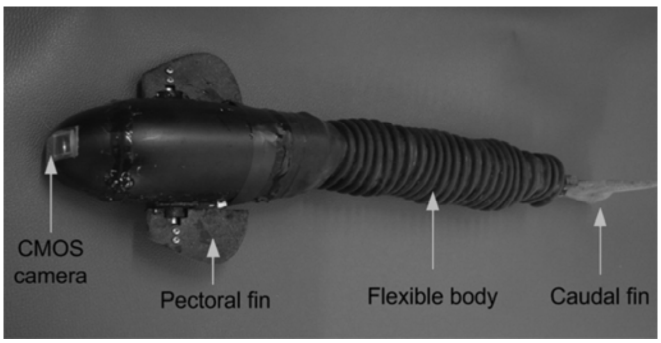

Figure 1. Mechanical configuration of a free-swimming robotic fish.

Table 1
Mechanical Parameters of the Robotic Fish with Embedded Vision

Parameter	Value
Size ($L \times W \times H$)	Approx. $517 \times 160 \times 78\,\mathrm{mm}^3$
Total mass	Approx. 1.3 kg
Number of pectoral fins	2
Number of joints	4
Sensors	CMOS camera, accelerometer/gyroscope
Power source	7.4 V, 3,000 mA h
Communication mode	Radio frequency 418–455 MHz

In accordance with the elaborate mechanical configuration, a hardware architecture is also well designed. TI DM3730 integrates an ARM Cortex A8 (up-to 1 GHz) and an 800 MHz TMS320C64x+ DSP, which is specialized in the field of multimedia application. With the enhanced device architecture and the TI's advanced 45-nm process technology, TI DM3730 is centred in the control circuit. In particular, due to the powerful capability of data processing, DSP is implemented to tackle video data to capture target position. Loaded with an embedded Linux system, ARM is allocated to manage overall resources, handle sensory information integrated for motion control and further communicate with the host PC. A bidirectional wireless communication module RF200 (TTL, 418–455 MHz) is employed to transfer messages between the robotic fish and the host PC. If necessary, a WiFi module with high throughput capability and low power consumption (IEEE 802.11, 2.4 GHz) can be exploited for video surveillance. It is worth noting that the WiFi module is appropriate in the surface because signals have a rapid attenuation underwater. The PWM signals, which actuate multiple moving joints, are produced by the body wave model in STM32F407.

With the aid of the developed robotic prototype and the hardware circuits, the block diagram of the control system (see Fig. 2) is conceived to cope with active visual tracking cases. After the CMOS camera captures image information, target positioning will be implemented. A yawing angle, which is used as the input of directional control, will be calculated from visual perception. In the directional control, yawing angles measured by the gyroscope are available as continuous feedback. The body wave model that describes contour features of fish swimming is employed. Moreover, a fuzzy logic controller is developed to generate input signals for servo motors. To integrate the agile locomotion and control accuracy, continuous image-based servo control is divided into directional control with multiple stages.

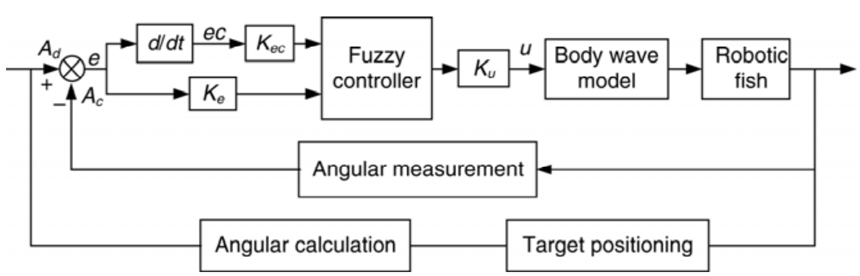

Figure 2. Block diagram of tracking control designed for the robotic fish with embedded vision.

3. Stability Control for the Biomimetic Robotic Fish

Though the robotic fish is an excellent paradigm to create high-performance underwater vehicles, its agility poses a great challenge to steady imaging. The camera is generally amounted in the head of a robotic fish with embedded vision. Since the head of the biomimetic fish is a passive mechanical part, the steady imaging entirely depends on the stability of the head. This section will investigate the issue of stability control, which is based on hydrodynamic model and parameter optimization.

It is inevitable that motion models are dominant for locomotion of the robotic fish. Motion models of the robotic fish, which cover the central pattern generator (CPG) model [16]–[18] and the body wave model [19], [20], are generally inspired by fish swimming. Each neuron (i.e., servo motors in the robotic fish) and neuronal connections are concerned in the CPG model, which takes advantages of simple parameters and convenient regulation. However, it is formidable to estimate attitudes of the fish. On the contrary, the body wave model intuitively reflects attitudes of the fish in the process of swimming, which contributes to stability control of the head.

The body wave model was first introduced by Lighthill when the slender body theory was studied [20]. Its basic form can be described in (1):

$$y_{\mathrm{body}}(x,t) = (c_1 x + c_2 x^2)\sin(kx - \omega t) \tag{1}$$

where y_{body} stands for the transverse displacement, x indicates the displacement along the main axis, c_1 represents the coefficient of the linear wave amplitude envelope, c_2 represents the coefficient of the quadratic wave amplitude envelope, k is the wave number, and ω denotes the frequency of the body wave. The parameter set (c_1, c_2, k, ω) can be regulated for desirable swimming modes.

According to Liu *et al.* [21], the traditional model of the fish body wave is improved to enhance stability of the head. After a tangent of x is subtracted at the point $x=0$, the improved model is shown in (2).

$$\begin{aligned}\tilde{y}_{\mathrm{body}}(x,t) &= y_{\mathrm{body}}(x,t) - c_3 x \frac{\partial y_{\mathrm{body}}(x,t)}{\partial x}\Big|_{x=0} \\ &= (c_1 x + c_2 x^2)\sin(kx - \omega t) + c_3 c_1 x \sin(\omega t)\end{aligned} \tag{2}$$

where c_3 is a scale factor, which can be used to adjust the amplitude of the body wave envelope. Eventually, the adjusted amplitude can conform to characteristics of fish-swimming kinematics. The other parameters are the same as those described in (1).

The improved body wave model can reduce the head swing, but it cannot yet guarantee steady imaging. Hence, it is a feasible solution to establish a hydrodynamic model based on the Newton-Euler method and optimize parameters of the body wave model. This solution can ensure steady imaging and meet control accuracy.

In addition, hydrodynamics are modelled based on a Newton-Euler method. Parameters in the hydrodynamics model are optimized on the basis of the genetic algorithm, which is employed to minimize the swing of the head. The specific method of the stability control is investigated in [22].

4. Directional Control of Robotic Fish

Modularized function designs make it available to separate the image processing, resource management and motion control, which improves efficiency of the control system. However, there exists the fact that different processors have discrepant processing abilities and different modules run programs in disparate periods. Thus, continuous image-based servo control encounters a tough problem of synchronous coordination. To tackle this problem, the continuous image-based servo control is divided into multi-stage directional control with visual inputs. It can not only promote each processor to maximum efficiency but also reduce resource consumption.

4.1 Visual Positioning

It is difficult for recognition and continuous positioning in aquatic environments, especially in the case of embedded systems with limited resources. In general, the artificial landmarks can facilitate visual recognition and positioning. In order to improve real-time performance, colour patches are generally selected as landmarks. However, colour attenuation is severe in aquatic environments [23]. In addition, the pixel values vary drastically when the distance of the object alters.

Hence, a colour set with colour patches arranged according to a specific topological relation is employed to achieve robust positioning. The artificial landmark used in this paper is shown in Fig. 3. To detect a single colour – red or blue, its main component is disposed. This detection is based on loose thresholds (weak detection). On the basis of the strict topological relation of different colours, a strong detection then follows to orientate the centre of the artificial landmark, i.e., the target position. This recognition strategy is inspired by the idea of strong and weak classifiers in the AdaBoost algorithm [24]. It should be remarked that the visual perception is designed to be carried out in multiple stages. Therefore, a simple searching method is adopted by scanning the rows and columns respectively. Moreover, interlaced scan is employed to enhance the searching efficiency.

Figure 3. The artificial landmark designed for tracking control.

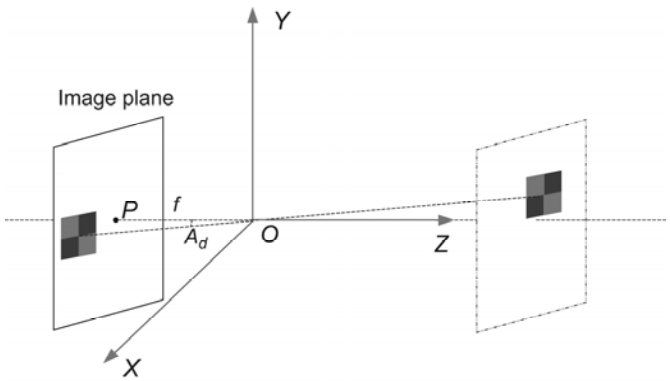

Figure 4. Imaging model used to calculate the yawing angle.

After positioning, the yawing angle A_d is calculated according to the pinhole imaging model (see Fig. 4). The origin of the camera coordinate system $OXYZ$ is set in the optical centre of the camera lens and the axis Z is defined as optical axis.

The yawing angle can be calculated according to (3).

$$\tan A_d = \sqrt{\left(\frac{u-u_0}{f_x}\right)^2 + \left(\frac{v-v_0}{f_y}\right)^2} \tag{3}$$

where (u, v) is the image coordinate of the landmark centre. (u_0, v_0) is the image coordinate of the camera's principal point. (f_x, f_y) denotes the magnification coefficients from the imaging plane coordinates to the image coordinates.

4.2 Directional Control Based on Fuzzy Logic

As stated previously, the improved body wave model is proposed for the biomimetic robotic fish. The input for the body wave model is determined by visual perception, yet a sound nonlinear model is missing. In such a situation, a fuzzy logic controller [25] is well suitable because it is essentially equivalent to a nonlinear PD controller. As depicted in Fig. 2, a directional motion control based on the fuzzy logic controller is developed. The input error $e(k)$ and the derivative of the input error $ec(k)$ are defined as follows:

$$\begin{cases} e(k) = A_d - A_c(k) \\ ec(k) = e(k) - e(k-1) \end{cases} \tag{4}$$

where A_d denotes the yawing angle derived from visual perception and $A_c(k)$ is the yawing angle measured by the gyroscope. The yawing angle is applied as negative feedback in order to guarantee the stability of the system. K_e, K_{ec}, and K_u represent the scale factors of $e(k)$, $ec(k)$, and $u(k)$, respectively.

The membership functions, the rule base and the defuzzication method compose the design of the fuzzy logic controller. In this paper, standard trigonometric functions are adopted as the membership functions, the rule base is designed on experience and the centre-of-gravity defuzzication method is employed. The specific design is described in [12].

4.3 Design of Control Strategies

Inspired by biological fish, the robotic fish is well designed to accomplish agile and efficient locomotion. However, it is inevitable that the agile locomotion can incur poor imaging quality, even vague imaging, which will immensely impact control accuracy. Due to these considerations, reasonable control strategies are proposed, which allows agile locomotion on the premise of ensuring control accuracy.

4.3.1 Continuity and Discreteness of Control

The first control strategy is concerned with continuity and discreteness. The inputs from visual perception are discrete and multi-staged while directional control is continuous. A communication protocol is employed to connect the discrete inputs and continuous directional control. This strategy decomposes the complex control into relatively independent and simple control. It can coordinate disparate processing abilities of different processors and ultimately guarantee a rapid implementation of the control system.

4.3.2 Stages of Control

Moreover, the tracking control is developed into multiple stages. The process of tracking consists of yawing stages and forward stages. Specifically, the yawing angle is obtained from visual information, which is followed by yawing control. Once the goal yawing is accomplished, the forward swimming is switched for a fast arrival at the target. Yawing control is on the premise of optimized parameters deprived from the stability control, which brings to steady imaging in the yawing stage. The normal swimming parameters are employed in the forward stage to realize fast swimming.

4.3.3 Integration of Strong Constraint and Weak Constraint

As is stated previously, directional motion control is equivalent to a nonlinear PD control, which cannot eliminate errors absolutely and yet takes an advantage of rapidness. As a result, this weak control is still implemented in the directional control. On the other hand, the yawing input from visual perception is of high precision, which adds a strong constraint to the control system. By virtue of this advantage, precise yawing angles are provided in multiple stages. This strategy, with a combination of a strong constraint from visual perception and a weak constraint in the directional control, can ensure the fish to accomplish a rapid and accurate tracking.

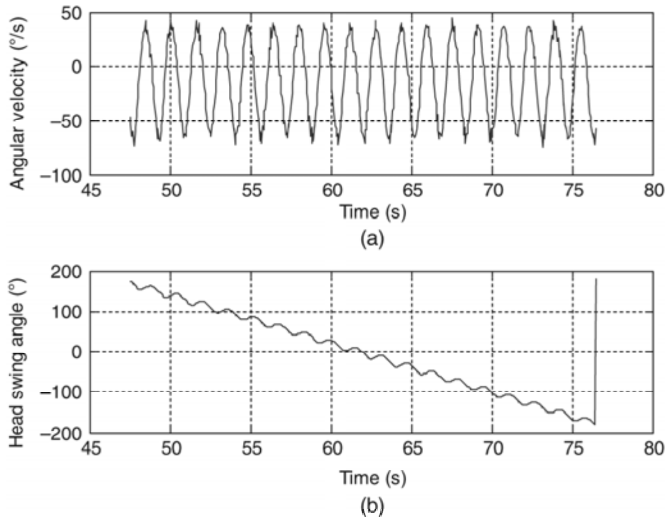

Figure 5. The head swing before optimization when the fish swam in a circle: (a) the angular velocity of the head and (b) the head swing angle.

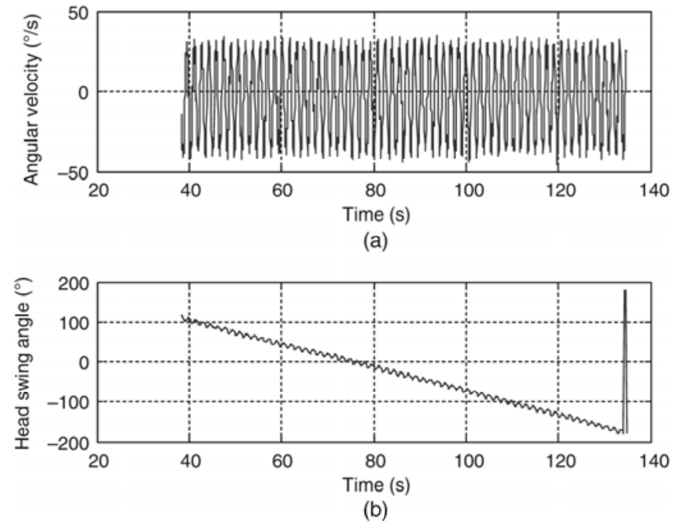

Figure 6. The head swing after optimization when the fish swam in a circle: (a) the angular velocity of the head and (b) the head swing angle.

5. Experimental Results and Discussion

5.1 Stability Control for the Biomimetic Robotic Fish

The proposed algorithm of the stability control has been verified in a free-swimming robotic fish, whose mechanical parameters are described in Table 1. As shown in Figs. 5 and 6, the head swing was measured when the fish swam in a circle. The swing angles measured by the gyroscope produced a mutation in 76.41 s (see Fig. 5), which is attributed to a restricted measurement range of the gyroscope. The situation in Fig. 6 is the same. The experimental results illustrate that the swing amplitude and angular velocity after optimization are suppressed. Specifically, the swing amplitude decreases from 13.59° to 7.90°, and the swing angular velocity also decreases from 73.42°/s to 41.32°/s. The results indicate that the proposed stability control method is reliable and effective, contributing to steady image data acquisition. Note that yawing control is significant in completing goal-oriented tasks based on embedded vision, especially the directional control with multiple stages investigated in this paper.

In addition, sequences captured by active vision before optimization and those after optimization can be observed intuitively in Fig. 7, where the target swing in the camera view was also estimated. $D_i (i=1,2)$ denotes the swing distance in the camera view and $L_i (i=1,2)$ represents the size of the object. The measurement unit is pixels. The estimated results are $\frac{L_1}{D_1}=6.46$ and $\frac{L_2}{D_2}=5.52$, which further proves that the stability control is favourable to steady image data acquisition.

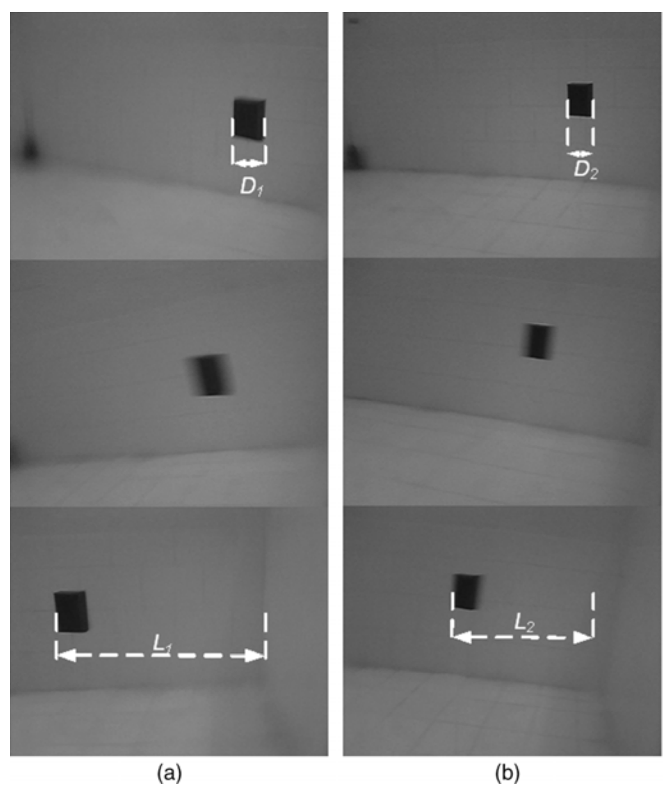

Figure 7. The target swing in vision field of the robotic fish: (a) the swing before stability control and (b) the swing after stability control.

5.2 Tests of Tracking Accuracy

Tests of tracking accuracy were carried out in an indoor pool with the dimension of $4 \times 5\,\mathrm{m}^2$. The artificial landmark was set as the object, which was recognized automatically and positioned continuously and then guided the robotic fish to swim. Note that the object position is only perceived by a monocular camera, yawing angles are measured by a gyroscope and any human intervention is not permitted. Through repeated trials, errors are measured when the fish reaches the artificial landmark. The

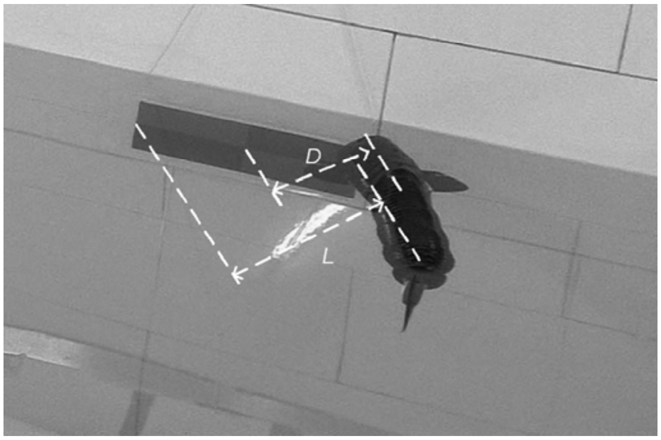

Figure 8. Illustration of error measurement.

method of error measurement is illustrated in Fig. 8, where D indicates the distance between the fish body and the centre of the landmark in the perpendicular direction of the camera optic axe and L represents the length of the landmark in the perpendicular direction of the camera optic axe. According to this definition, the error analysis results are summarized in Table 2.

It is generally thought that the relative error within $[-0.5,\ 0.5]$ satisfies goal-oriented tasks. Experimental results reveal that the proposed control algorithms can guarantee accurate tracking, which is dominantly benefited from the refined control strategies. With continuous generation of desired yawing angles from visual perception, the strong constraints of the control system can sustain control accuracy. In addition, the weak constraints in the directional control diminish deviations in succession, restrain error accumulation after multiple stages and eventually alleviate the complexity of the strong constraints.

5.3 Anti-interference

Furthermore, a disturbance that gives rise to an off-course of the robotic fish is purposely introduced to highlight the reliability and robustness of proposed algorithms. In order to solve this interference problem, a tracking framework (see Fig. 9) is well developed.

The experimental conditions are the same as those in tests of tracking accuracy. Figure 10 illustrates a complete

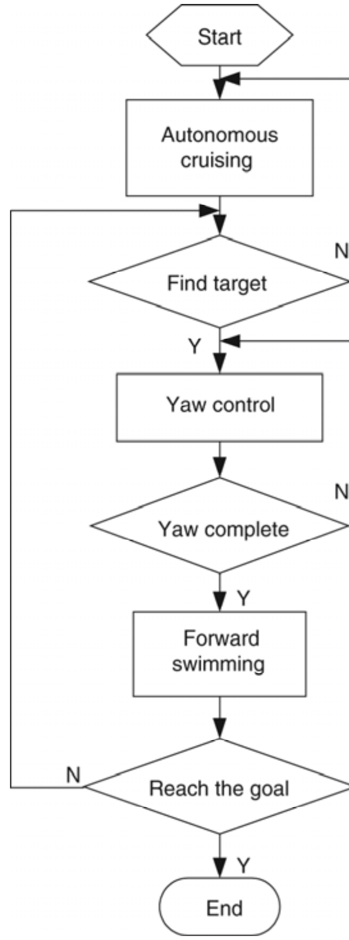

Figure 9. The flowchart about the anti-interference tracking.

snapshot sequence of automatic recognition, autonomous tracking, and anti-interference swimming. The robotic fish firstly autonomously cruised to recognize the target. After the target position determined, the fish was yawing to the goal direction (from 6″ to 8″). A sudden disturbance was factitiously introduced (in 10″), which resulted in an off-course. Afterwards, visual recognition and positioning that was followed by yawing adjustment were triggered again (from 14″ to 17″). Note that the robotic fish might miss the target in the case that visual positioning failed (in 22″). The robust algorithm guided the robotic fish to autonomously cruise to search the target again until the fish determined the position and swam to the target.

Table 2
Analysis of Tracking Error

Trial No. (#)	1	2	3	4	5	6	7	8	9	10
D/L (pixels)	12/50	0/16	10/47	5/108	41/89	0/13	13/37	9/41	13/83	15/45
Relative error	∼0.24	0	∼0.21	∼0.054	∼0.46	0	∼0.35	∼0.22	∼0.16	∼0.33
Average value	∼0.20									
Variance	∼0.17									

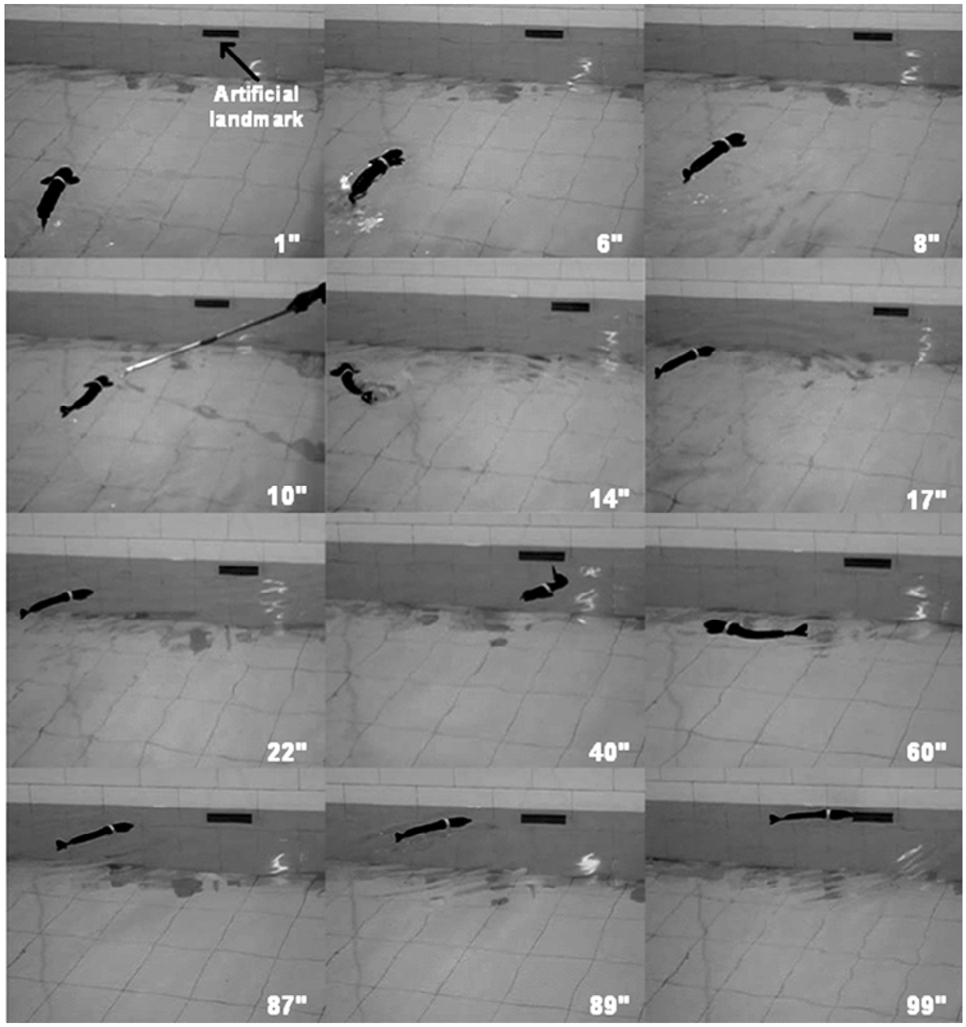

Figure 10. Snapshot sequence of an automatically positioning, tracking, and anti-interference swimming.

6. Discussion

The moment that a factitious disturbance intervenes covers the stage of directional control and that of forward swimming. Specifically, when a disturbance intervenes the directional control, the directional control based on the fuzzy logic can restrain this disturbance and keep the fish swimming to the goal direction. In the stage of forward swimming, the perturbance might cause the fish to miss the target. To deal with this situation, the visual algorithm is proposed to make the fish cruise for searching the target until the target is detected again. In this sense, whenever the perturbance occurs, the proposed algorithms can suppress interference and avoid tracking failure. In addition, the robustness of the algorithms also lies in that the robotic fish can autonomously cruise for recognition and position continuously even when visual positioning fails.

Even though the directional control can dispose positioning failure, it still endures enormous costs of time and energy to locate the target again. Given that the proposed algorithm of stability control can only minimize the head swing, rather than fundamentally eliminate this swing, there are several aspects remained to be optimized. The improvement of the mechanical structure and motion compensation via pectoral fins offer an integrative and radical solution. On the one hand, the mechanical structure can be perfected by increasing a cushioning in the head. On the other hand, analysing the impact of the pectoral fins on hydrodynamics of fish swimming and coordinating locomotion of the pectoral fins with that of the caudal fin can compensate for the head swing.

7. Conclusion and Future Work

Implementing vision-guided tracking for a flexible robotic fish is a challenging task. In this paper, an active tracking method based on the artificial landmark is presented in order to propel a robotic fish to track the target in 2-D space. Specifically, a method of stability control is proposed to minimize the head swing for steady image data acquisition. Moreover, a visual algorithm of automatic recognition and positioning is put forward on the basis of an artificial landmark. Furthermore, a robust control framework with the properties of multiple stages and directional control is presented to provide an integrative solution for agile and accurate swimming. Finally, experiments were conducted in a free-swimming robotic fish with embedded vision, demonstrating that the proposed algorithms are effective and feasible.

Future work will focus on the navigation control based on visual perception in 3-D space. The improvement of the mechanical structure lays a foundation of steady and agile movement in 3-D space. In the meantime, 3-D visual positioning based on the artificial landmark will be further explored.

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