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# Expert S-surface control for autonomous underwater vehicles

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**Abstract:** S-surface control has proven to be an effective means for motion control of underwater autonomous vehicles (AUV). However there are still problems maintaining steady precision of course due to the constant need to adjust parameters, especially where there are disturbing currents. Thus an intelligent integral was introduced to improve precision. An expert S-surface control was developed to tune the parameters on-line, based on the expert system, it provides S-surface control according to practical experience and control knowledge. To prevent control output over-compensation, a fuzzy neural network was included to adjust the production rules to the knowledge base. Experiments were conducted on an AUV simulation platform, and the results show that the expert S-surface controller performs better than an S-surface controller in environments with currents, producing good steady precision of course in a robust way.

**Keywords:** autonomous underwater vehicle; S-surface control; expert control; intelligent integral; fuzzy neural network

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## 1 Introduction

An underwater vehicle is a strongly nonlinear system with closely coupled motion with six degrees of freedom. Meanwhile, due to the complex and changeable oceanic environment, non-linear problems will exist in the design of its control system, which should be robust and adaptive. S-surface control method, proposed in Ref.[1], combining the idea of fuzzy control and the structure of PD control, simplifies the design of the controller and guarantees the non-linear control effect. In order to improve the vehicle's operating performance, Ref.[2] added self-learning ability to S-surface controller in terms of the back-propagation algorithm in neural network. To reduce the subjective uncertainties in the process of design, immune-genetic algorithm was utilized in Ref.[3] to optimize the tunable parameters of S-surface controller. All the methods above obtain good effect according to the experimental results, however some deficiencies still exist. For instance, in Ref.[2], the precise teacher supervising signal is usually difficult to be obtained. In view of the requirement of hardware speed and real-time system, the method presented in Ref.[3] is difficult to be applied to underwater vehicles' on-line control system. Since many investigations for S-surface control have been done and lots of experience have been acquired, an expert S-surface control approach, combining expert system technology[4-8] and S-surface control, is proposed in this paper. In the method, control strategy is constructed in accordance with the operating experience and the production rules, and an expert controller is used to adjust the tunable parameters on-line to improve the performance.

## 2 S-surface control model based on intelligent integral

The traditional mathematical model of S-surface controller is shown as

$$u = 2.0/[1.0+\exp(-k_1 e - k_2 \dot{e})] - 1.0 + \Delta u , \qquad (1)$$

where $e$ and $\dot{e}$ represent the input information of the controller (error and rate of error change in normalized form); $u$ is the output of the controller, which stands for the force in each degree of freedom (normalized); $k_1$ and $k_2$ represent respectively the control parameters of $e$ and $\dot{e}$; $\Delta u$ is the value (normalized) of the steady disturbance force obtained in adaptive method. Since the ocean current and unknown disturbance can be taken as steady

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disturbance force in some time, $\Delta u$ is used to shift S-surface to eliminate the steady error. Actually, $\Delta u = k_i \int e dt$ is an integral term.

Although the model of S-surface controller is robust, the system steady-state precision of the controller is bad since it's essentially a PD controller[7]. In order to increase the precision, integral method is commonly used to reduce the steady-state error. Usually, the integral parameter $k_i$ is difficult to be selected, for a larger $k_i$ will make the system vibrate, and a smaller one will not help. Additionally, "integral saturation" caused by continual integral will occur if there is an error, which decreases the system rapidity.

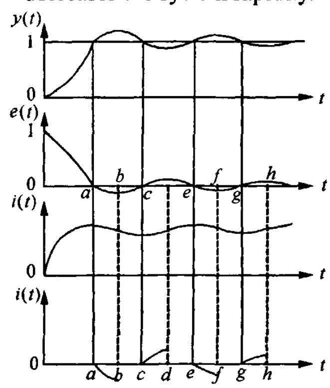



Fig.1 Curves of error $e(t)$ and error integral $i(t)$

The reason for the bad effect of the above integral control is that the integral does not incarnate the control decision idea of the experienced operator. In the integral curve intervals $[a, b]$ and $[b, c]$ shown in Fig.1, the integral effect is opposite to the control effect of experienced operator. While there is system overshoot, the correct control strategy is that a minus control quantity is needed to reduce the overshoot and error as soon as possible. However, the integral control in this interval increases a positive control quantity, since the integral result in interval $[0, a]$ is hard to counteract, and the symbol is hard to change, which keeps the integral control quantity positive. Therefore, the system overshoot cannot be reduced rapidly and the transient time is extended.

In the integral curve interval $[c, d]$, the integral action increases a positive control quantity, which is advantageous for decreasing backward adjustment of the output. However, in interval $[d, e]$, the integral action continues to strengthen, which will result in another system overshoot. And the integral action at this time hinders the effective control for the system.

In order to overcome the disadvantages of the integral control above, another integral curve shown as Fig.1 is used, which indicates the integral action in intervals $[a, b]$, $[c, d]$ and $[e, f]$, etc. The integral can promptly provide correct additional control quantity for integral control, and restrain the increment of system error effectively; Meanwhile in intervals $[0, a]$, $[b, c]$ and $[d, e]$, integral action is paused to transfer the system to steady state by inertia. At this time, the system is not out of control, it's also restricted by the proportional control.

The nonlinear integral with artificial intelligence, which memorizes only the useful information instead of useless data, well imitates man's memory behavior and artificial intelligent control strategy, so it is called artificial intelligent integral control.

According to the above analysis, the judgment condition of intelligent integral is described as: when $e \cdot \dot{e} > 0$, carrying on integral for the error; when $e \cdot \dot{e} < 0$, stopping integral. It is the basic condition for intelligent integral. Then the comprehensive condition of intelligent integral, in accordance with extreme points of the error and error change (boundary condition), is illustrated as follows:
When $e \cdot \dot{e} > 0$ or $\dot{e} = 0$ and also $e \neq 0$, there is integral for the error;

When $e \cdot \dot{e} < 0$ or $e = 0$, there is no integral.

The integral above is the so-called intelligent integral action, which can improve the system steady-state precision. Thus, the S-surface control model with intelligent integral is

$$\begin{cases} u = 2.0/[1.0 + \exp(-k_1 e - k_2 \dot{e})] - 1.0 + k_i \int e dt, \\ \qquad\qquad e \cdot \dot{e} > 0 \text{ or } \dot{e} = 0 \text{ and } e \neq 0; \\ u = 2.0/[1.0 + \exp(-k_1 e - k_2 \dot{e})] - 1.0, \\ \qquad\qquad e \cdot \dot{e} < 0 \text{ or } e = 0. \end{cases} \tag{2}$$

## 3 Expert control

Expert control, also called expert intelligent control, is an important branch of intelligent control field. So far, there is no explicit definition for expert control. And the sketchy definition of expert control is the system control combining control theory and technology with those of expert system in unknown environment with imitation of expert intelligence. Professor Cai Zi-xing, a famous expert in intelligent control area, defines expert control system as follows: the control system, imitating the control knowledge and experience of human experts, with application of expert system conception and technology, is called expert control system or expert controller[8].

First of all, before constructing expert controller, the control knowledge from control expert in specific field and the experience knowledge from the operators should be handled and transformed to the language that can be accepted by machines. Then the handled knowledge is stored in knowledge base, from which the inference engine invokes the knowledge (or rules) to infer. And the inferred knowledge is stored in knowledge base, meanwhile it is outputted to control rule set to match control rules and control the plant. The output of the plant, as a feedback signal which feeds back to the information acquisition and processing element, is used as the new information compared with the set value. Then the real-time adjustment is completed with repetition of the steps above—continuing checking, acquiring new data and control outputs.

Generally, the expert controller consists of information acquisition and processing element, knowledge base, inference engine and control rule set. The structure of a typical expert controller is shown in Fig.2.

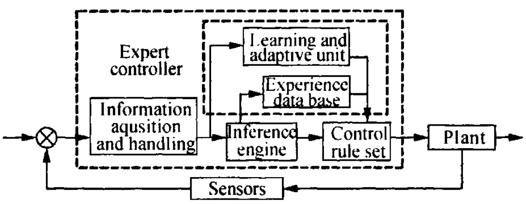


Fig.2 Structure of expert controller

# 4 Expert S-surface control

## 4.1 Structure of expert S-surface control system

There are only three controlling parameters ($k_1$, $k_2$ and $k_i$) of S-surface control model in Eq.(2), so it's simpler to tune these parameters than those of fuzzy control. The overshoot and convergence rate of the system can be adjusted via the percentages of $e$ and $\dot{e}$ in control output, which could be altered by changing the values of $k_1$ and $k_2$. And the steady-state error will be quite small if setting a proper $k_i$.

The presented expert S-surface control, as an indirect expert control system based on expert knowledge, is an intelligent control combining the technology of expert system with S-surface control. In the system, the experiential knowledge and the production rules obtained during solving control problems are applied to constructed control strategy, and $k_1$, $k_2$, $k_i$ can be tuned on-line in accordance with system behavior to obtain a good system performance. Expert S-surface controller is a secondary-level real-time intelligent coordinate controller, which consists of basic control level and expert intelligent coordinate level, as shown in Fig.3. In the basic control level, real-time control is achieved in terms of a closed loop composed of S-surface controller and the plant; and the expert intelligent coordinate level, which consists of data base (where is the error, threshold of error change ratio, adjustment range of $k_1$, $k_2$ and $k_i$, and each group of parameters), knowledge base (production rules) and intelligent coordinator (inference engine), on-line monitors the behavior of the control system and tunes the parameters of S-surface controller with the help of inference engine according to system knowledge and evidence.

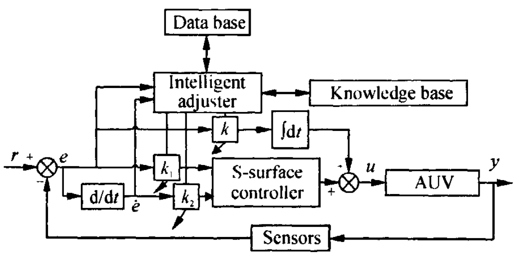


Fig.3 Structure of expert S-surface control system

## 4.2 Knowledge base based on fuzzy neural network

The analysis of the effect of $k_1$ and $k_2$ in S-surface controller to the system is depicted as follows, and $k_1$ affects the effect of error $e$. A larger $k_1$ enhances the control effect of errors, which leads to slower convergence with shorter rise-time and larger overshoot, and even vibration if worse, so $k_1$ should not be a large value. Contrarily, a smaller $k_1$ decreases the control effect of error $e$, which is helpful to diminish the overshoot, however, if $k_1$ is too small, the effect of errors will be greatly weakened, which also results in slower convergence with longer rise-time and larger steady-state error.

$k_2$ affects the effect of error change ratio $\dot{e}$. A larger $k_2$ enhances the effect of $\dot{e}$, improves the sensitivity of S-surface controller and restrains overshoots. Whereas if $k_2$ is too large, the system will be over sensitive to the change of $\dot{e}$, and the control effect of $\dot{e}$ is advanced, thus the system response time is increased. Contrarily, if $k_2$ is too small, the sensitivity of the controller will be weakened, which is harmful to restrain the overshoot.

It can be concluded from the analysis above that the effect of $k_1$ on system response differs from that of $k_2$. And even for the same system at different stages, the effects of $k_1$ and $k_2$ are different.

Based on the analysis and the experience about the control system, fuzzy neural network is used to fit the production rules in knowledge base and tune the parameters $k_1$, $k_2$ and $k_i$ on-line in case of the jump of control outputs.

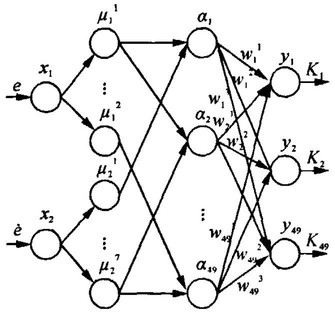


Fig.4 Structure of fuzzy neural network

A four-layer feedforward network shown in Fig.4 is used. The inputs are respectively position error $e$ and velocity $\dot{e}$, and the outputs are adjustment weights $K_1$, $K_2$, $K_3$. The first layer is input layer, where $x_1 = e$, $x_2 = \dot{e}$. The second layer is fuzzification layer, in which there are respectively 7 Gauss membership functions $\mu_i^j = \exp[-\frac{(x_i - m_{ij})^2}{\sigma_{ij}^2}]$ corresponding with $e$ and $\dot{e}$, where $i = 1,2$, $j = 1,2,\cdots,7$. The Third layer is rule layer, where $\alpha_k = \mu_1^m \cdot \mu_2^n$, $m$=1,2, $\cdots$,7, $n$=1,2,$\cdots$,7, so there are 49 nodes here. The fourth layer is output layer with three outputs $y_1$, $y_2$, $y_3$ corresponding with the adjustment weights $K_1$, $K_2$, $K_3$. $w_i^j$ represent the rules of adjustment weight, $i$=1,2,$\cdots$,49, $j$=1,2,3.

This network equals a fuzzy system in functional way, and it is easy to be depicted and convenient to introduce the self-learning algorithm. The fuzzy language variables of $e$ and $\dot{e}$ belong to the fuzzy set {NL,NM,NS,ZE,PS,PM,PL}. The rules $w_i^j$ are shown as follows:

**Table 1 Rules for $K_1$**

| $\dot{e}$\\$e$ | NL | NM | NS | ZE | PS | PM | PL |
|---|---|---|---|---|---|---|---|
| NL | 3.0 | 2.2 | 1.3 | 0.0 | 0.3 | 1.2 | 2.0 |
| NM | 2.8 | 2.0 | 1.2 | 0.0 | 0.5 | 1.3 | 2.2 |
| NS | 2.7 | 1.8 | 1.0 | 0.0 | 0.7 | 1.5 | 2.3 |
| ZE | 2.5 | 1.7 | 0.8 | 0.0 | 0.8 | 1.7 | 2.5 |
| PS | 2.3 | 1.5 | 0.7 | 0.0 | 1.0 | 1.8 | 2.7 |
| PM | 2.2 | 1.3 | 0.5 | 0.0 | 1.2 | 2.0 | 2.8 |
| PL | 2.0 | 1.2 | 0.3 | 0.0 | 1.3 | 2.2 | 3.0 |

**Table 2 Rules for $K_2$**

| $\dot{e}$\\$e$ | NL | NM | NS | ZE | PS | PM | PL |
|---|---|---|---|---|---|---|---|
| NL | 1.0 | 1.7 | 2.3 | 3.0 | 2.3 | 1.7 | 1.0 |
| NM | 0.7 | 1.3 | 2.0 | 2.7 | 2.0 | 1.3 | 0.7 |
| NS | 0.3 | 1.0 | 1.7 | 2.3 | 1.7 | 1.0 | 0.3 |
| ZE | 0.0 | 0.7 | 1.3 | 2.0 | 1.3 | 0.7 | 0.0 |
| PS | 0.3 | 1.0 | 1.7 | 2.3 | 1.7 | 1.0 | 0.3 |
| PM | 0.7 | 1.3 | 2.0 | 2.7 | 2.0 | 1.3 | 0.7 |
| PL | 1.0 | 1.7 | 2.3 | 3.0 | 2.3 | 1.7 | 1.0 |

**Table 3 Rules for $K_3$**

| $\dot{e}$\\$e$ | NL | NM | NS | ZE | PS | PM | PL |
|---|---|---|---|---|---|---|---|
| NL | 3.0 | 3.0 | 3.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| NM | 3.0 | 3.0 | 3.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| NS | 3.0 | 3.0 | 3.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ZE | 3.0 | 3.0 | 3.0 | 0.0 | 3.0 | 3.0 | 3.0 |
| PS | 0.0 | 0.0 | 0.0 | 0.0 | 3.0 | 3.0 | 3.0 |
| PM | 0.0 | 0.0 | 0.0 | 0.0 | 3.0 | 3.0 | 3.0 |
| PL | 0.0 | 0.0 | 0.0 | 0.0 | 3.0 | 3.0 | 3.0 |

After the fuzzy neural network-based knowledge base is constructed, $k_1$, $k_2$, $k_i$ are tuned according to the formula as follows:

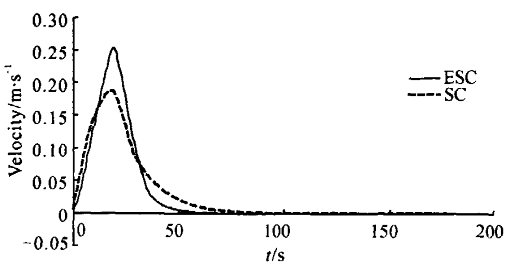
$$\begin{cases} k_1 = \alpha + \lambda_1 K_1, \\ k_2 = \beta + \lambda_2 K_2, \\ k_i = \gamma + \lambda_3 K_3, \end{cases} \tag{3}$$

where $\alpha$, $\beta$, $\gamma$ represent the initial values of $k_1$, $k_2$, $k_i$, $\alpha = \beta = 3.0$, $\gamma = 0$; $\lambda_i$ ($i$=1,2,3) is the restriction factor, $\lambda_1 = 0.1$, $\lambda_2 = 0.08$, $\lambda_3 = 0.01$.

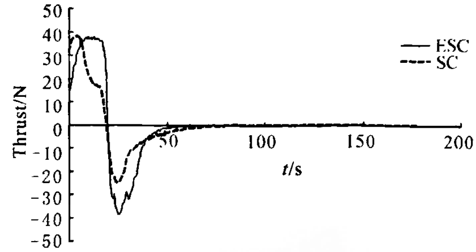
## 5 Simulation experiment

The experiments are conducted on the simulation platform of an AUV developed by our lab. The AUV, as a platform on which AUV motion control, path planning and target identification are investigated, consists of motion control system, path planning system, navigation system, emergency management system and monitor system. There are 8 thrusters in the propelling system, including 4 ducted propellers located at the stern and 4 tunnel propellers located on the body. At the stern, the two horizontally located propellers each with a maximal thrust of 210 N are used as main thrusters, and the other two is utilized to provide trim moment. There are respectively two tunnel propellers used as vertical thrusters and lateral thrusters. Due to smaller velocity, the motion in each degree of freedom can be decoupled, and a single controller is used for the motion in one degree of freedom, while the coupled action among the degrees of freedom can be taken as external disturbance. In order to obtain a more precise motion model, numeral simulation frequency is set to 10 Hz, and to simulate the practical instance that is restrained by the data frequency of the actual sensors located on the AUV, the controller simulation frequency is set to 2 Hz.

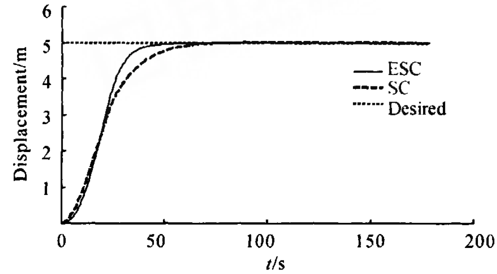
The velocity, thrust and position response curves of longitudinal position control and vertical position control in still water are shown in Figs.5 and 6 respectively. The initial state of AUV is 0, and the target points are respectively 5 m in longitudinal direction and 5 m in vertical direction. It can be concluded in the two figures that the expert S-surface controller has faster response speed compared with S-surface controller. However the system steady-state precision is improved little, since S-surface controller has good steady-state precision in still water as well.



(a) Longitudinal velocity response curves

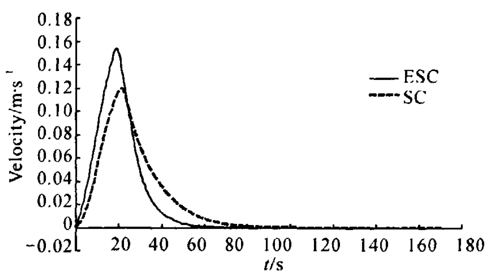


(b) Longitudinal thrust response curves

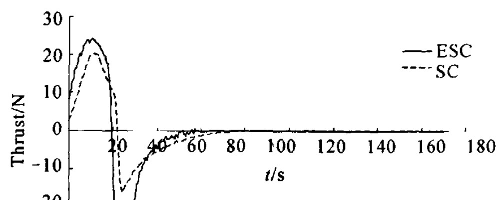


(c) Longitudinal position response curves

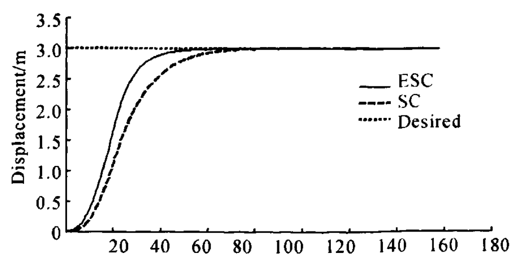
Fig.5 Longitudinal position control



(a) Vertical velocity response curves



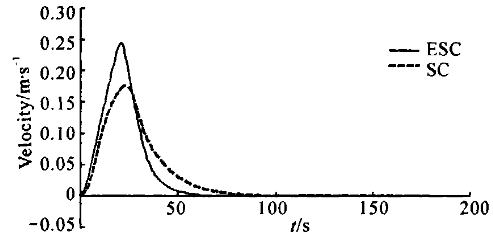
(b) Vertical thrust response curves



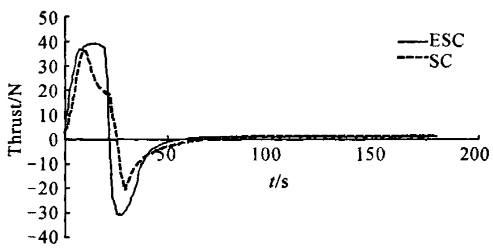
(c) Vertical position response curves

Fig.6 Depth control

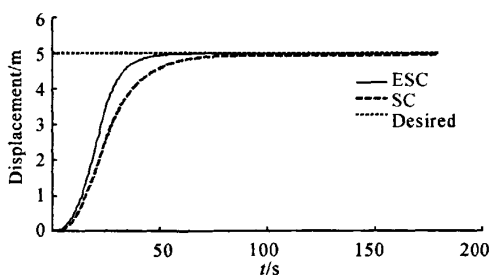
To prove the capability of expert S-surface controller against current disturbance, the position control experiment in current environment is conducted. In view of the motor ability, the heading of the AUV is set to the reverse direction of the current when there is current. Velocity, thrust and position response curves of longitudinal position control in current environment are shown in Figs.7 and 8.




(a) Longitudinal velocity response curves



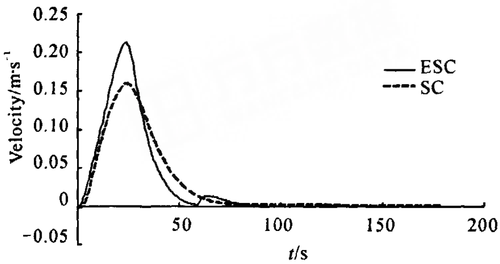

(b) Longitudinal thrust response curves



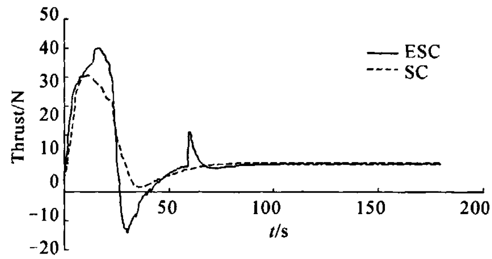

(c) Longitudinal position response in 0.1 m/s current

Fig.7 Longitudinal position control in 0.1 m/s current

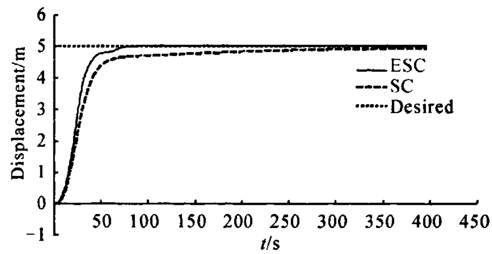
The initial state of AUV is 0, and the target point is 5 m in longitudinal direction. The current speeds in Figs.7 and Fig.8 are respectively 0.1 m/s and 0.3 m/s (the speed is large for the AUV), and the current angles are both 180°. In Fig.8(b), the curve of ESC has a jump at about 60 s, the reason is that there's an adaptive unit to help the controller handle fixed disturbance. And at that time, the effect of current is large for the vehicle, the output of the adaptive unit increases obviously. However, the control system can handle the jump by itself. It can be concluded from the two figures in current environment, especially under large current disturbance, expert S-surface controller has faster response speed and better steady-state precision. The ability of expert S-surface controller against current disturbance is better than that of S-surface controller.




(a) Longitudinal velocity response curves




(b) Longitudinal thrust response curves




(c) Longitudinal position response in 0.3 m/s current

Fig.8 Longitudinal position control in 0.3 m/s current

## 6 Conclusions

S-surface control is proved to be available in the application to motion control of underwater vehicles. In this paper, an expert S-surface control is presented combining expert system technology and S-surface control, and its feasibility and advantage are validated by some simulation tests on a certain simulation platform. The expert S-surface controller can adjust its parameters on-line in different navigation situations, thus the ability of anti-inference is enhanced, and the system response speed is increased, meanwhile, the steady-state precision and stability of the system are also guaranteed.

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