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Analysis on AUV Heading Control System Based on RS-Chaos-LSSVM

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Abstract: Aimed at the submarine uncertainties and model's impreciseness, an integrated RS-Chaos-LSSVM model is put forward because of nonlinearity and time-variability of AUV heading control system. The LSSVM is a typical nonlinear regression modeling based on small sample. Its parameters are optimized by Chaos algorithm. It is to gain the optimal model and get the higher accurate. By using Rough theory the monitor data attribute of AUV is reduced to eliminate the redundant information to improve efficiency. Taken a certain typed AUV as an example, the two controller compare results .The results show the RS-Chaos-LSSVM controller markedly reduce the time. And the heading error and control rudder are simulated in the ideal and ocean current environment. In the ideal environment the two controllers all have good performances. But in the ocean current environment the simulation results show the integrated controller improve the model's stability and accuracy. The overshoot, the rise and adjust time reduced greatly. In a word the integrated RS-Chaos-LSSVM heading predictive controller has better performances especially strong anti-interfere capability.

Keywords: AUV, Heading Control, RS, LSSVM, Chaos optimization.

1. Introduction

Since last decades, AUV (Autonomous Underwater Vehicle) has gradually replaced part of people's labor in the special works, such as dirty, tired, bitterness, dangerous or repetitive etc. It has developed more widely, more intelligence. Thus it is necessary to design an autonomous and precise heading control system.

In reference [1] AUV was dynamically controlled by using a PID controller. The results are valid. But it cannot compensate for un-modeled hydrodynamic forces or unknown disturbances dynamically. And the parameters need rich experience to be determined. Reference [2] described the NN was used in the heading control. The simulation accuracy results are satisfied. But the poor real time is a really problem, the system stability and convergence have the ascension of the larger space. Reference [3] involved the Fuzzy PID controller. It was relatively simple and easy to determine the unknown parameters. However, to the parameter fluctuations the real-time robustness was not strong and the subjective factors were introduced. The sliding mode controller was introduced to control the AUV yaw control in reference [4]. The simulation results showed that the method had good robustness on the un-modeled dynamics and uncertainty environmental parameters. But there existed dithering phenomenon and it belonged to off-line control. And as the AUV is a long development cycle and high cost. The heading control is a typical of small sample condition problem of pattern recognition. Combined with the characteristics of various methods the AUV heading control based on RS-Chaos-LSSVM is forward.

The LSSVM (Least Square Support Vector Machine, LSSVM) has good generalization ability, small sample of control, fast calculation speed, nonlinear system modeling. It is a powerful tool. But it has a direct influence on the parameters of the control effect. The model's parameters are optimized by using COA (Chaos optimization algorithm), which is to control the heading model accurately. The redundant information is reduced by using RS (Rough Sets). The extracted decision rules are used to train LSSVM model. So the AUV heading control model can be built by RS-Chaos-LSSVM. It is to explore a new effective control method.

The rest of the paper is organized as follows. The next section is AUV heading model. The RS-Chaos-LSSVM Model is in the Section 3. The RS theory and the LSSVM algorithm model are brief introduced. And the Chaos-LSSVM and the RS-LSSVM Predictive Model are given, respectively. The AUV heading control is in the Section 4. It is the key part. It contains an identifier LSSVM identifier and a controller LSSVM controller. In Section 5 the analysis simulation results are given to demonstrate the compound RS-Chaos-LSSVM heading controller. In Section 5, conclusions are drawn.

2. The AUV Heading Model

It is vital to the AUV heading control especially far sailing. The integrative controller to a certain control law must be driving course control actuators-vertical rudders. It makes it run in the prior planning path according to a certain performance index.

2.1. AUV Heading Control System Model

A pair of rudder located on the AUV rear as the main actuator to the heading control. The Fig. 1 is the AUV heading control system organization chart. The whole control system consists of AUV uncertain nonlinear dynamics model, measure parts, heading controller, vertical rudders and some disturbing factors such as wave and current etc.

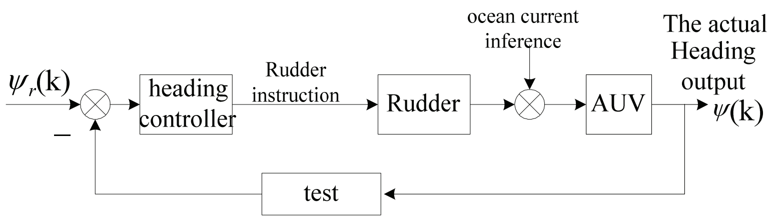

Fig. 1. The organization chart of the AUV heading control system.

2.2. AUV Nonlinear Mathematic Model

An AUV complete six degree-of-freedom mathematical model can be found in reference [1] and [12]. They are surge, sway, roll, pitch heave, and yaw motion equation. Suppose the couple between horizontal and vertical plane is omitted. It is very convenient that research two motions, respectively. The horizontal plane motion equations can be simplified formula are as follows.

$$(m+\lambda_{11})\dot{u} = T - C_{xs}\frac{1}{2}\rho v^2 S \tag{1}$$

$$\begin{aligned}&(m+\lambda_{33})\dot{v}_z - (mx_c+\lambda_{35})\dot{\omega}_y\\&= mv_x\omega_y + \frac{1}{2}\rho v_T^2 S(C_Z^{\beta}\beta + C_z^{\delta_r}\delta_r + C_z^{\bar{\omega}_y}\bar{\omega}_y)\end{aligned} \tag{2}$$

$$\begin{aligned}&(J_{yy}+\lambda_{55})\dot{\omega}_y - (mx_c+\lambda_{35})\dot{v}_z + mx_c v_x\omega_y\\&= \frac{1}{2}\rho v_T^2 SL(m_y^{\beta}\beta + m_y^{\delta_r}\delta_r + m_y^{\bar{\omega}_y}\bar{\omega}_y)\end{aligned} \tag{3}$$

$$\dot{\varphi} = \omega_y \tag{4}$$

$$\dot{X}_0 = v_x\cos\varphi - v_z\sin\varphi \tag{5}$$

$$\dot{Z}_0 = -v_x\sin\varphi + v_z\cos\varphi \tag{6}$$

$$v = \sqrt{{v_x}^2 + {v_z}^2} \tag{7}$$

$$\beta = \arctan(\frac{v_z}{v_x}) \quad , \tag{8}$$

where v_x (m/s) is the horizontal speed, v_z (m/s) is the vertical velocity, ω_y (rad) is the rotation angular velocity of Y axis, β (deg) is the sideslip angle, θ (deg) is the pitch, ψ is the yaw φ (deg) and the roll φ (suppose $\varphi = \omega_x \neq 0$), X_0 (m) is the x component, Y_0 (m) is the y component, δ is the rudder angle, ρ (kg/m^3) is the density of water, λ

is the additional mass, m is the mass of AUV, L is the long of vehicle, S is the surface area of AUV, J is the rotational inertia [12].

3. The RS-Chaos-LSSVM Model

The LSSVM is the typical nonlinear system, fast calculation modeling based on the AUV small sample. The LSSVM parameters can be optimized by using the Chaos theory. The control stability accuracy has improved. But the identification control speed is greatly reduced. Rough set can reduce the attribute value. The system real time can be improved.

3.1. The RS Theory

The RS theory can extract the decision rule set by reducing knowledge, eliminating redundant information and seek the questions of the classification rule set in the premises of keeping the classification without any prior knowledge [5]. So it is widely applied to the pattern recognition of various pattern identifications.

The Fig. 2 shows the establishment of RS-LSSVM predictive model. The acquired data of AUV are reduced by using RS theory to obtain an extracted rule set. It can be used to train LSSVM model. The trained model can be adopted to control AUV's heading motion.

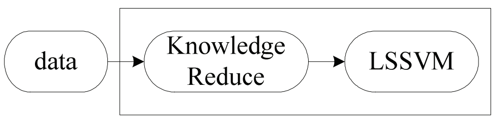

Fig. 2. The RS-LSSVM predictive control model.

The acquired data can be mapped as a knowledge retrieval system $S = <U, A, V, f>$, where U is an universe, $A = C \bigcup D$ is the attribute set, subset C is called as the conditional attribute, D is called as the decision attribute, $C \bigcap D = \varnothing$, $V = \bigcup_{r \in R} V_r$ is the attribute value set, V_r represents the value of the attribute r, $f : U \times R \to V$ is an information function. The steps of knowledge reduction can be described as follows [5].

Input the knowledge system S with the conditional attribute set $C = \{a_1, a_2, \cdots a_n\}$ and the decision attribute set $D = \{Dec\}$.

Step1: calculate C positive field $pos_C(D)$ in D;

Step2: eliminate the attribute a_i, $C_t = C - \{a_i\}$ from C;

Step3: calculate C_t positive field $pos_{C_t}(D)$ in D;

Step4: if $pos_{C_t}(D) = pos_C(D)$, then wipe out a_i, else remain a_i;

Step5: repeat traverse all attributes according to the procedures above.

Output one of the relative reductions of the conditional attribute set C to the decision attribute D.

3.2. The LSSVM Algorithm Model

Least Squares linear System is leaded in SVM. It replaces the traditional quadratic programming, aims to solve the question of the classification and function estimation. The system has the advantages of high procession-precision, stabilized performance, high speed. The structure drawing as followings:

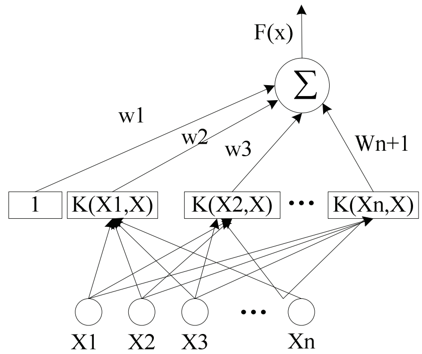

Fig. 3. The structure drawing of the LSSVM algorithm.

LSSVM algorithm has the advantages of high procession precision and stable performance [7]. The rule set extracted by using RS is taken as the input of LSSVM to train it. Suppose the training sample is a n-dimensional vector, N samples form the sample set D, {($D = \{(x_i, y_i) | i = 1, 2, \cdots N\}$), $x_i \in R^n$ $y_i \in R$, where x_i is an input data, and y_i the corresponding output value. LSSVM can map the data into a high dimensional feature space by using a nonlinear mapping ϕ. Then, the equation of linear regression is

$$y(x) = w^T \phi(x) + b, \quad (9)$$

where $\omega \in R^{n_h}$ is the weight vector, b is the constant bias.

The learning process can be translated into an optimization problem according to the principle of structural risk minimization.

$$\min J(w, e) = \frac{1}{2} w^T w + \frac{1}{2} C \sum_{i=1}^{N} e_i^2$$

$$\text{s.t. } y_i = w^T \varphi(x_i) + b + e_i, \; i = 1, 2, \cdots N$$

$\varphi(x): R^n \to R^{n_h}$ is a mapping function in the kernel space, $e_i \in R$ is the error variance, J is the loss function, C is the adjustable regularized parameter.

A Lagrangian function can be introduced to solve the above optimization problem, which can transform the optimization with constraint to the optimization without constraint.

$$L(w,b,e;a) = J(w,e) - \sum_{i=1}^{N} \alpha_i (w^T \varphi(x_i) + b + e_i - y_i) , \tag{10}$$

where $\alpha_i \in R$ is the Lagrangian multiplier. The partial derivatives of L with respect to ω , b , e_i and α_i are found out according to Karush-Kuhn-Tucker (KKT) condition. The middle variables ω and e_i are eliminated, and the solution of α_i and b can be obtained

$$\begin{bmatrix} 0 & \eta \\ s & \Omega + \gamma^{-1} I \end{bmatrix} \begin{bmatrix} \alpha \\ b \end{bmatrix} = \begin{bmatrix} 0 \\ Y \end{bmatrix},$$

where
$\Omega \in R^{N \times N}$, $\Omega_{km} = \phi^T(x_k)\phi(x_m)$, $Y = [y_1, \cdots, y_N]^T$, η is the N-dimensional column vector, namely, η =[1…N]), $\alpha = [\alpha_1, \cdots a_N]$, I is the confirmed matrix, s is the N-dimensional row vector, namely, $s = [1 \cdots N]^T$. So the function estimation can be expressed as

$$\hat{y}(x) = \sum_{i=1}^{N} \alpha_i K(x_i, x_j) + b , \tag{11}$$

where $K(x_i, x_j)$ is the kernel function that meets Mercer requirements. Gaussian radial basis function (RBF) is selected as the kernel function in this paper.

$$K(x_i, x_j) = \exp(-\left\| x_i - x_j \right\|^2 / 2\delta^2) , \tag{12}$$

where δ is the kernel factor, i.e. the width of the kernel function.

3.3. The LSSVM Algorithm Model

The LSSVM model's parameters are optimized by COA (Chaos optimization algorithm). The regularized parameter C and the kernel factor δ are very important. The chaos theory can optimize the parameters of LSSVM model. The LSSVM parameters are acted as the combinatorial optimization problem. And then the objective function is built on it. The chaotic state brings to the optimization variables by similar carrier wave. The ergodic scope of chaotic motion extends to the upper and lower limits of the optimizing variable. A more detailed explanation follows below. Define the optimization problem as

$$\min J = \min f(z_i) = \frac{1}{L} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{13}$$

$$s.t. \;\; C \in [C_{\min}, C_{\max}], \sigma \in [\sigma_{\min}, \sigma_{\max}] , \tag{14}$$

where y_i is the $i-th$ known sample output value of the samples $\{x_i, y_i\}_{i=1}^N$, $\hat{y}_i$ is the output prediction of the former, which can be calculated from equation (11), $f(z_i)$ is the regression of LSSVM, z_i is the optimized variable.

Logistic mapping is chosen to produce the chaos variables.

$$x_{n+1} = \mu x_n (1 - x_n) \tag{15}$$

where the initial value $x_0 \in (0,1)$, and x_0 is not equal to 0.25, 0.5 or 0.75.

Logistic mapping is a full mapping in interval (0,1) when $\mu = 4$, a system goes into chaos state. x_n is the ergodic in the interval $(0,1)$.

It can be seen from (11) and (12) that the objective function J of the optimization problem (13) is the function of C and δ . J will decrease and converge to its minimum J^* if searching ergodicly in C and δ definition domains by using the chaos variable. The corresponding minimum C^* and δ^* will be the optimal parameters of the LSSVM. Specific Chaos-LSSVM algorithm procedure is as follows.

Step1: Initialization. Input data: sample set $\{x_i, y_i\}_{i=1}^N$, optimization number A1 (large number), $n1 = 0$, the optimal index J^* (appropriate positive), two random number in the $(0,1)$ interval x1, x2;

Step 2: Generating chaotic variables. The n chaotic variables $x_{n,i}$ are selected by carrier-wave way. The n optimization variable generating chaotic variables $z_{n,i}$ are introduced, respectively. Then

$$x_i^* = z_i^*$$

$$z_{n,i} = c_i^r + d_i^r x_{n,i} \tag{16}$$

Step 3: Iterative search chaotic variables.

If $f(z_{n,i}) < f^*$, then $f^* = f(z_{n,i})$, $z_i^* = z_{n,i}$ else abandon $z_{n,i}$;

Step 4: In turn iteration $n = n + 1$;

$$x_{n,i} = \mu x_{n-1,i} (1 - x_{n-1,i}) ;$$

Step 5: Repeat step2-4 till it remains unchanged so far in a certain step 2;

Step 6: If $n < A1$, then turn to step 2;

Step 7: return to the optimal δ^* and C^* , α_i and b .

3.4. The RS-LSSVM Predictive Model

The AUV depth predictive control flow chart shows in the Fig. 4.

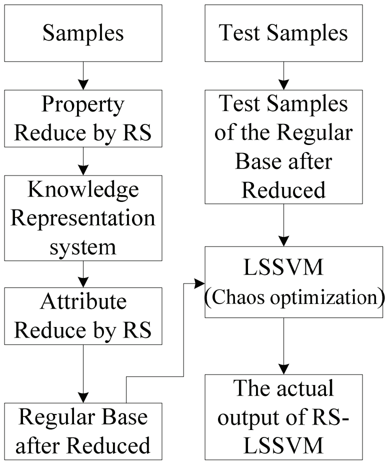

Fig. 4. The AUV predictive algorithm flow chart of RS-LSSVM.

1) Analysis the collect data, select the sample set;
2) Attribute value reduction form the knowledge representation system by the RS;
3) Attribute reduction to the knowledge representation system form the extract regulated set by the RS;
4) The LSSVM model is build. The appropriate kernel function and the parameters are determined by the chaos theory. The reduced rules set train the LSSVM model till the satisfied result.
5) The RS-LSSVM predictive model is tested and verified by the test samples.
6) The whole predictive results analysis.

4. The RS-Chaos-LSSVM Model

The LSSVM model is the kernel of the heading control system. It contains an identifier LSSVMI and a controller LSSVMC.

4.1. The AUV LSSVMI

The vehicle heading motion model is approximated by using LSSVMI. Its inputs are the actual heading signals $\psi(k)$, rudder signal $\delta(k)$ and roll angle $\varphi(k)$.

$$\begin{aligned} X = [&\psi(k), \psi(k-1), \cdots \psi(k-n+1), \delta(k-1), \cdots, \\ &\delta(k-m+1), \varphi(k), \varphi(k-1), \cdots, \varphi(k-p+1)], \end{aligned} \tag{17}$$

where n, m and p are the orders of yaw, rudder and roll signals, respectively. The output of LSSVM model is the system output yaw signal, namely heading signal. Given the train samples

$$\{(X_1, \psi_1), (X_2, \psi_2), \cdots, (X_l, \psi_l),\} \subset R^N \times R\,,$$

$$X_1, X_2, \cdots, X_l$$

as the input vector at $k+l-1$, they are denoted as

$$\begin{aligned} X_1 = [&\psi(k), \psi(k-1), \cdots \psi(k-n+1), \delta(k-1), \cdots \\ &\delta(k-m+1)], \varphi(k), \varphi(k-1), \cdots, \varphi(k-p+1)] \end{aligned} \tag{18}$$

$$\begin{aligned} X_2 = [&\psi(k), \psi(k+1), \cdots \psi(k-n+2), \delta(k), \cdots \\ &\delta(k-m+2)], \varphi(k+1), \varphi(k), \cdots, \varphi(k-p+2)] \end{aligned} \tag{19}$$

……

$$\begin{aligned} X_l = [&\psi(k+l-1), \psi(k+l-2), \cdots \psi(k-n+l) \\ &\delta(k+l-2), \cdots, \delta(k-m+l)], \varphi(k+l-1), \\ &\varphi(k+l-2), \cdots, \varphi(k-p+l)] \end{aligned} \tag{20}$$

where $\psi_1, \cdots, \psi_l$ is the output from $k-1$ to $k+l-1$, namely, $\psi_1 = \psi(k-1), \cdots, \psi(k+l-1)$.

The AUV heading predictive control model is obtained according to equation (11).

$$\psi_m(k) = f(X(k)) = \sum_{k=1}^{n} \alpha_k K(X(i), X(k)) + b \tag{21}$$

4.2. The AUV Integrated LSSVMC System

The AUV Chaos-LSSVM close-loop control scheme mainly governs the heading control of AUV, as shown in Fig. 5.

In Fig. 5 the $\psi_r(k)$ is the preset heading value. The rudder $\delta(k)$ is the controlled quantity. The $\psi(k)$ is the actual yaw angle. The LSSVM model parameters are optimized by Chaos theory. The AUV input is the weight sum between LSSVMC and LSSVMI.

$$\delta(k) = \beta\delta_L(k) + (1-\beta)\delta_C(k)\,, \tag{22}$$

where $\delta_L(k)$ is the LSSVM output model. $\delta_C(k)$ is the LSSVMC output of the Chaos optimizing. β is the identification accuracy factor of the LSSVM.

The online modified model parameters are predictive by using the chaos LSSVM. The accurate heading control is obtained. The LSSVM model is build according to the historical data before starting up. The model parameters C , σ , α_i and b are saved in the CPU. After the running, the present moment controlled and the output variable covers the previous data.

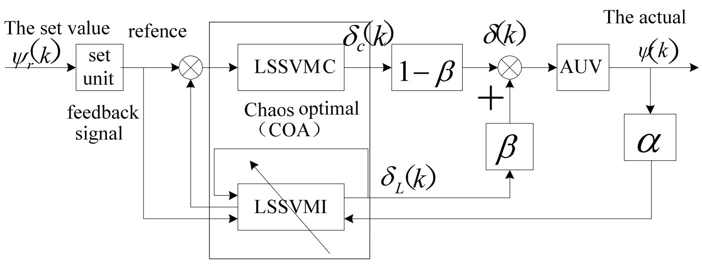

Fig. 5. The vehicle heading control based on Chaos-LSSVM.

Every certain of the time the Chaos-LSSVM identifier updated sample set and build the new model. At the next sample time the new model is substitute for the older one. The sufficient stability and accurate are ensured. So the AUV dynamical model is online learning by the RS-LSSVMI. It is constantly approximation the nonlinear mapping characteristics. The RS-LSSVMC gives the control signal. It makes the AUV heading control satisfying precision according to the random instructions.

4.3. The RS-Chaos-LSSVM Heading Model

The predictive model based on RS-Chaos-LSSVM is shown in Fig.. 6. The bigger left, big left, small left, less left, keeping, less right, small right, big right and bigger right form the control decision attribute set D . The yaw, rudder and ocean current etc. form the conditional attribute set C . The classification can be conducted in two steps. First, the redundant attributes are removed in the sample pretreatment. The invalid data are eliminated. The attribute of data set are reduced by using rough sets theory. Second, the LSSVM training model is established. It will further classify the reduced data; the results and the classification accuracy are outputted. They are as shown in Fig. 6.

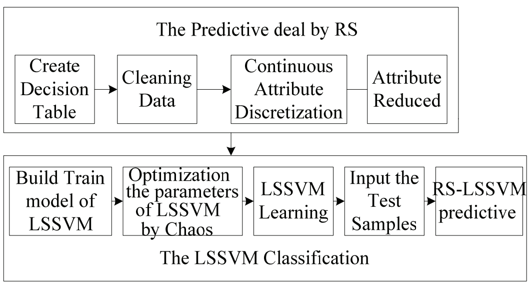

Fig. 6. The heading prediction method based on RS-Chaos-LSSVM

5. The Analysis of Simulation Results

To verify the RS-Chaos-LSSVM heading controller's effectiveness, taking a certain vehicle as objective, the yaw control simulation is conducted. Set the horizontal rudder is [-35^o ~ +35^o]. The average speed is about 2 m/s. the given heading angle is 20^o. Select 300 data as the training samples, the other 200 data as the test samples. The simulation results are described as follows.

5.1. The Compare between Chaos-LSSVM and RS-Chaos-LSSVM Controller

To improve the real timing the AUV integrated heading controller is put forward between the RS theory and Chaos-LSSVM. The Table 1 shows the heading simulation time results between the Chaos-LSSVM and RS-Chaos-LSSVM controller in the foregoing environment.

Table l. The compare results between Chaos-LSSVM and RS-Chaos-LSSVM.

	Train error	Test error	Test time	Train time
Chaos-LSSVM	0.1087	0.1682	89.91s	64.65s
RS-Chaos-LSSVM	0.1102	0.1697	62.13s	36.88s

The Chaos-LSSVM controller has the good performance for the special model. Such as the dynamic un-model, model inaccurate, interference or other uncertain factors. But the learning convergence speed is slow. It is difficult to meet the real-time control requirements. The RS theory is fused. Namely it is the integrated RS-Chaos-LSSVM controller. It can save about the half train and test time. The scheme markedly improves the control performance of the AUV heading control.

5.2. The Heading Control Simulation in Ideal Environment

Suppose there is no current interference. The certain AUV heading control simulation results are as shown in below Figs. 7, 8 and 9 in the foregoing environment, respectively.

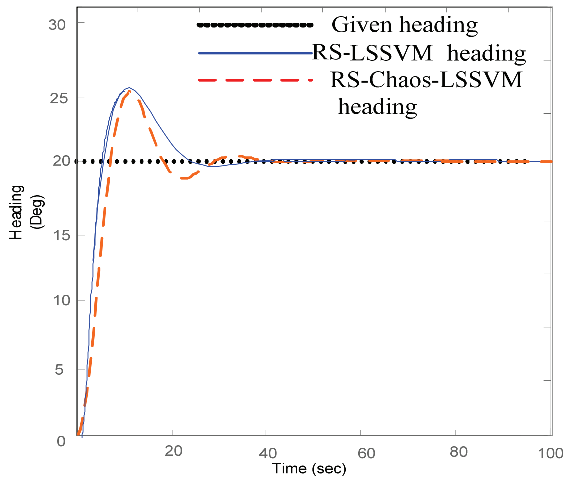

Fig. 7. The heading controller based on RS-LSSVM and RS-Chaos-LSSVM without interference.

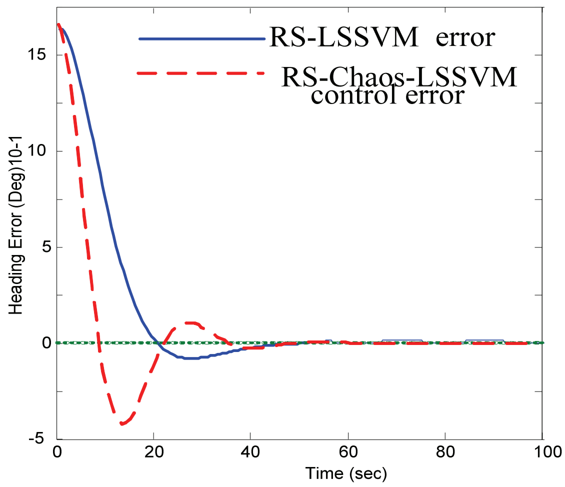

Fig. 8. The heading error controller based on RS-LSSVM and RS-Chaos-LSSVM without interference.

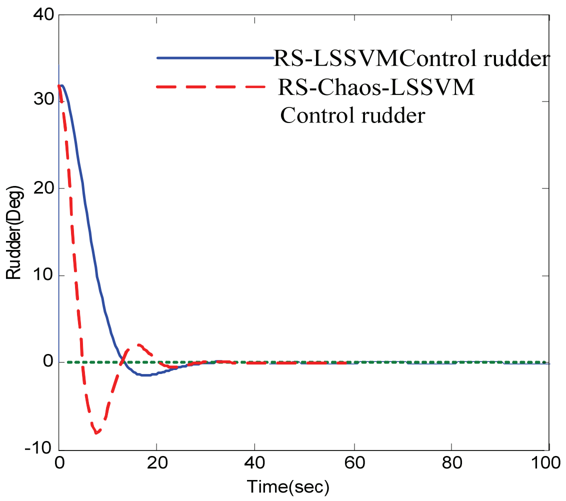

Fig. 9. The control rudder based on RS-LSSVM and RS-Chaos-LSSVM without interference.

The two max yaw angles are all approximately 25^0. The both overshoot are about 25 %. And that the RS-LSSVM controller has a bit faster tracking speed. The RS-Chaos-LSSVM and RS-LSSVM controller stabilization time is about 45 s and 38 s, respectively (see Fig. 7, the heading error in the RS-LSSVM controller is significantly less than the RS-Chaos-LSSVM one. The error is approximately 5 and 2 degree, respectively (see Fig. 8), the RS-LSSVM controller steering varying instruction is not much easier than the RS-Chaos-LSSVM (see Fig. 9).

In short conclusion the RS-LSSVM heading controller has little better performance than the comprehensive one in ideal environment.

5.3. The Heading Control Simulation in Ocean Current Environment

There are some disturbance ocean currents. Such as suppose ocean current is 60^o, the 2 sea wave power. The given yaw angle is the 20^o. The both simulation curves are as following Figs. 10, 11 and 12.

There are external environment interferences. The hydrodynamic coefficient affects the model, which is not precise. So the RS-LSSVM heading controller has the bigger errors than the RS-Chaos-LSSVM. In the Fig. 10 the yaw angle accurate of the RS-Chaos-LSSVM heading controller has the better than the other one. The overshoot of the RS-LSSVM heading controller is about 50 %. The other one is only 15 % yet; the two adjust time is 25 s and 75 s, respectively (see Fig. 10). The heading error of RS-LSSVM controller is about 9 degree, the other one is approximately 3 degree in the Fig. 11; The RS-LSSVM control rudder is bigger than the other one in the Fig. 12. From the three figures there are more the control yaw angle accurate and the robust in the RS-Chaos-LSSVM heading controller.

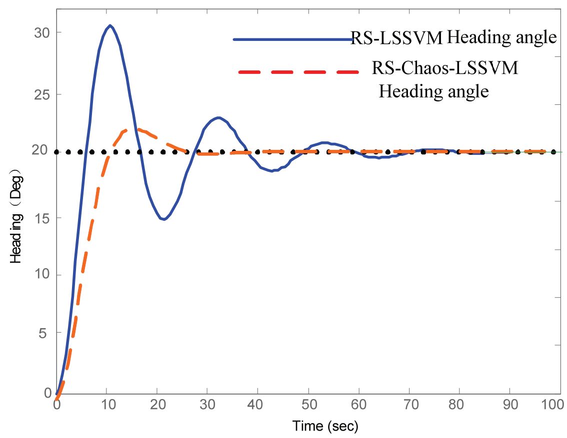

Fig. 10. The heading controller based on RS-LSSVM and RS-Chaos-LSSVM in ocean current environment.

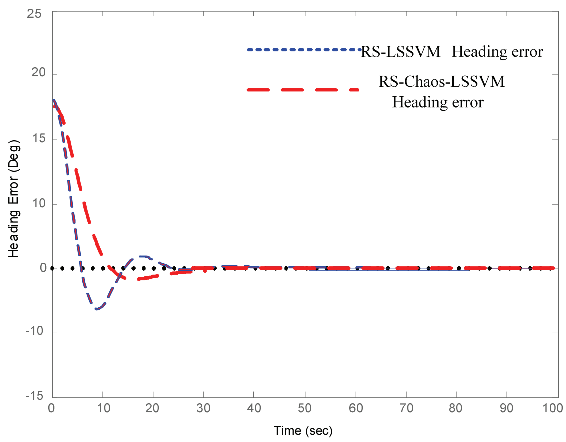

Fig. 11. The heading error controller based on RS-LSSVM and RS-Chaos-LSSVM in ocean current environment.

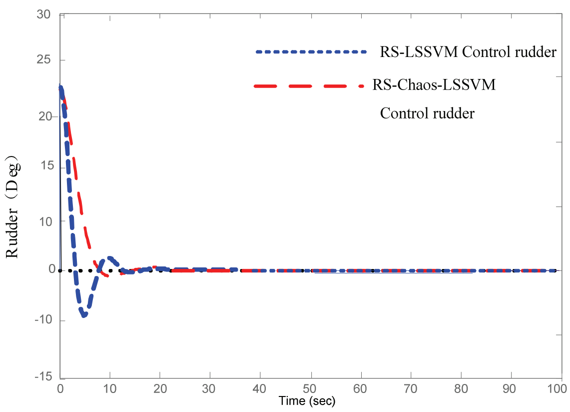

Fig. 12. The control rudder based on RS-LSSVM and RS-Chaos-LSSVM in ocean current environment.

In conclusion, suppose the AUV hydrodynamic coefficient is constancy, not vary. The outside current disturbing influences are ignored. The RS-LSSVM heading controller has good performances. But it is valid within a certain range of work; however the actual ocean current environment is very complicated. The control performances turn worse when the system model changed or dynamical imprecise. The RS-Chaos-LSSVM controller can realize the real-time online optimization control. The control performances are obviously superior to the RS-LSSVM one especially in special circumstances. Such as: dynamic un-modeled, uncertain inference etc.

6. Conclusion

The AUV heading control is the typical nonlinear system. The control research has very important theoretical and practical significance. Fused the RS, Chaos theory and LSSVM model, the integrated RS-Chaos-LSSVM controller has been forward. The optimal model has been ensured by using the Chaos theory in the ocean interference environment. The better stability and accuracy have been gained. The overshoot of the integrated RS-Chaos-LSSVM heading control is only 15 % in the ocean interference environment The RS theory can be attributing and attribute value reduction. The redundant information has been eliminated. The real time has been improved. The adjust time has been reduced about 50 second. The simulation results have been showed the integrated RS-Chaos-LSSVM heading control has the better control stability and accuracy, at the same time the good real time has been gained in the uncertain interference environment.

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