수중 자율 운동체의 방향 제어를 위한 자기회귀 웨이블릿 신경회로망 기반 적응 백스테핑 제어

Self-Recurrent Wavelet Neural Network Based Adaptive Backstepping Control for Steering Control of an Autonomous Underwater Vehicle

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Abstract : This paper proposes a self-recurrent wavelet neural network(SRWNN) based adaptive backstepping control technique for the robust steering control of autonomous underwater vehicles(AUVs) with unknown model uncertainties and external disturbance. The SRWNN, which has the properties such as fast convergence and simple structure, is used as the uncertainty observer of the steering model of AUV. The adaptation laws for the weights of SRWNN and reconstruction error compensator are induced from the Lyapunov stability theorem, which are used for the on-line control of AUV. Finally, simulation results for steering control of an AUV with unknown model uncertainties and external disturbance are included to illustrate the effectiveness of the proposed method.

Keywords : Self-Recurrent Wavelet Neural Network(SRWNN), adaptive backstepping control, autonomous underwater vehicle

I. Introduction

The advancements in the area of underwater robotics have been made over the past several years. However, from the view point of control, the dynamic models of autonomous underwater vehicle (AUV) are highly nonlinear and the hydrodynamic coefficients of vehicles are difficult to be accurately estimated a priori because of their variations in the different operating conditions. Therefore, the control systems of AUV must possess the ability of learning and adapting to the variation of dynamics and hydrodynamics coefficients of vehicles in order to provide the desired performance[1].

Until now, various control strategies have been presented for the motion control of AUVs. Goheen and Jefferys[2] proposed an adaptive control scheme for autopilots of autonomous and remotely operated underwater vehicles, and many researchers concentrated their interests on the applications of sliding mode control (SMC) methodology for the control of AUV[3-6]. In these literatures, the bounds of uncertainties were often assumed to be known a priori or neglected. Therefore, these methodologies have some limitation to the application of AUV.

Recently, the combined control schemes such as robust adaptive control have been presented for nonlinear uncertainty systems[7-10]. In most of literatures, neural networks, which mostly used to multi layer perceptron(MLP) were used for the approximation of unknown function. However, these were no adaptation scheme for unknown bounds of networks' weights values being introduced. Restricting condition and no adaptation schemes have problems in some practical applications due to the modeling inaccuracy.

On the other hand, self-recurrent wavelet neural network (SRWNN) was proposed to compensate the disadvantage of MLP [11] such as static mapping. SRWNN had the powerful dynamic mapping and simple structure.

In this paper, we present an SRWNN based adaptive backstepping control method for the autonomous steering control of an AUV systems, where the unstructured uncertainties are assumed to be unbounded, although they still satisfy certain growth conditions characterized by bounding functions. First, we introduce the AUV steering model whose uncertainties and disturbance are separated and then we design the adaptive backstepping controller of an AUV. In the proposed control system, the SRWNN is employed as the uncertainty observer in the adaptive backstepping controller. Also the error compensator is used to reduce the approximation error of SRWNN. The adaptation laws for training weights of SRWNNs and error compensators are induced from the Lyapunov stability theory, which are applied to guarantee the asymptotic stability of the proposed method. Finally, we simulate the steering control of an AUV to show the effectiveness of the proposed SRWNN based adaptive backstepping control system. This thesis is organized as follows. In Section 2, we introduce the model of AUV systems with uncertainties, and Section 3 discusses the SRWNN structure and the SRWNN based adaptive backstepping control for solving the robust control problem of the AUV systems. Here, the stability, robustness, and performance of the proposed control system are analyzed via the Lyapunov stability theorem. Simulation results are discussed in Section 4. Finally, Section 5 gives some conclusions.

II. Problem statements

1. Dynamic model of AUV system

The dynamical behavior of an AUV can be expressed through six degree-of-freedom (DOF) nonlinear equations as[12].

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) + d = \tau \qquad (1)$$

where, $q \in \Re^6$ is the position and orientation vector, $M \in \Re^{6\times6}$ is the inertia matrix (including added mass), $C_D \in \Re^{6\times6}$ is the matrix of Coriolis, centripetal and damping term, $G \in \Re^{6\times6}$ is

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the gravitational forces and moments vector, and $\tau \in \Re^{6\times 6}$ is a control input vector. $d \in \Re^{6\times 6}$ is a disturbance vector.

We describe the development of the steering model used to control the AUV, using the following assumptions:

Assumption 1[13]:

- The earth's rotation is negligible for the purposed of acceleration components of the vehicle center of mass
- The primary forces that act on the vehicle are inertial and gravitational in origin and are derived from hydrostatic, propulsion, thruster, and hydrodynamic lift and drag forces
- The vehicle behaves as a rigid body

And further simplifies equation of motion (EOM) of 6 DOF AUV with the following assumptions:

Assumption 2[14]:

- The center of mass of the vehicle lies below the origin (z_G is positive)
- x_G and y_G are zero
- The vehicle is symmetric in its inertial properties
- The motions in the vertical are negligible (i.e. $[w_r, p, q, r, z, \phi, \theta] = 0$)
- u_r equals the forward speed, u_0

Additionally, according to Assumptions 1 and 2, x component is decoupled and sway and heave velocities are also could be neglected. Under these assumptions, the yaw dynamics of AUVs could be expressed as follows:

$$\dot{\psi} = r \tag{2}$$

$$\dot{r} = F + B\delta_r + d_r \tag{3}$$

where, F and B can be defined as $F = \zeta_1(M, C_D, g)$, $B = \zeta_2(M)$ with $\zeta_1(\cdot)$ and $\zeta_2(\cdot)$, respectively, which are smooth functions, δ_r is a rudder plane angle shows Fig. 1 and d_r is external disturbance. Due to the highly nonlinear characteristic of AUVs' dynamics and the unpredictable operating environments of the vehicles, in the most applications of AUVs, it is difficult to determine the exact values. For this reason, we construct the following assumptions.

Assumption 3: F and B are smooth unknown functions, and B is nonzero with known sign. Without any loss of generality, we assume that $B > B_0 > 0$ with B_0 an unknown constant.

Under this assumption, the yaw dynamics of AUVs could be rewritten as follows:

$$\dot{\psi} = r \tag{4}$$

$$\begin{aligned} \dot{r} &= (\bar{F} + \Delta F) + (\bar{B} + \Delta B)\delta_r + d_r \\ &= \bar{F} + \bar{B}\delta_r + \Omega(q, \dot{q}, \delta_r) \end{aligned} \tag{5}$$

where, $\Omega(q, \dot{q}, \delta_r) = \Delta F + \Delta B\delta_r + d_r$, $\bar{F}$ and $\bar{B}$ are the nominal values, which are only known values for an AUVs, ΔF and ΔB denote the model uncertainties. That is, suppose that the actual values F, B and external disturbance d_r are the unknown values. Accordingly, the uncertainty term $\Omega(q, \dot{q}, \delta_r)$ cannot be computed.

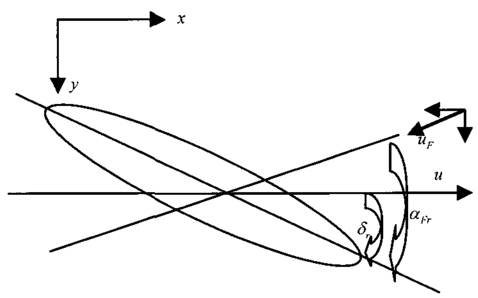


그림 1. 키 각.

Fig. 1. Rudder angle.

2. SRWNN structure

A schematic diagram of the SRWNN structure is shown in Fig. 2, which has N_i inputs, one output, and $N_i \times N_w$ mother wavelets[15,16]. The SRWNN structure consists of 4 layers: an input layer, a mother wavelet layer, a product layer, and an output layer. Each node of a mother wavelet layer has a mother wavelet and a self-feedback loop.

In this paper, we select the first derivative of a Gaussian function, $\phi(x) = -x\exp(-\frac{1}{2}x^2)$ which has the universal approximation property[17] as a mother wavelet function. The nodes in a product layer are given by the product of the mother wavelets as follows:

$$\Phi_j(x) = \prod_{k=1}^{N_i} \phi(z_{jk}), \quad \text{with } z_{jk} = \frac{u_{jk} - m_{jk}}{d_{jk}}, \tag{6}$$

where, m_{jk} and d_{jk} are the translation factor and the dilation factor of the wavelets, respectively. The subscript jk indicates the k-th input term of the j-th wavelet. In addition, the inputs u_{jk} of the wavelet nodes can be denoted by

$$u_{jk} = x_k + \phi_{jk} z^{-1} \cdot \theta_{jk}, \tag{7}$$

where, θ_{jk} denotes the weight of the self-feedback loop, and z^{-1} is a time delay. The input of mother wavelet layer contains the memory term $\phi_{jk} z^{-1}$, which can store the past information

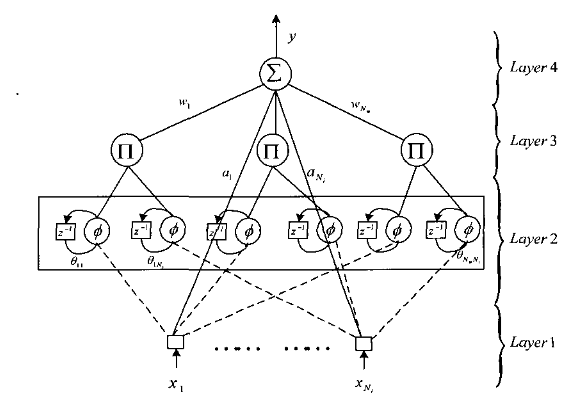


그림 2. SRWNN 구조.

Fig. 2. SRWNN structure.

of the network. That is, the current dynamics of the system is conserved for the next sample step. Thus, even if the SRWNN has less mother wavelets than the WNN, the SRWNN can attract the system with complex dynamics well. Here, θ_{jk} is a factor to represent the rate of information storage. These aspects are the apparent dissimilar point between the WNN and the SRWNN. Also, the SRWNN is a generalization system of the WNN because the structure of the SRWNN is the same as that of the WNN when $\theta_{jk}=0$. The SRWNN output is a linear combination of consequences obtained from the output of the product layer. In addition, the output node accepts directly input values from the input layer. Therefore, the SRWNN output y is composed of self-recurrent wavelets and parameters as follows:

$$y=\sum_{j=1}^{N_w} w_j \Phi_j(x)+\sum_{k=1}^{N_i} a_k x_k, \tag{8}$$

where, w_j is the connection weight between product nodes and output nodes, and a_k is the connection weight between the input nodes and the output node. In this paper, five weights a_k, m_{jk}, d_{jk}, θ_{jk} and w_j of the SRWNN are trained by the adaptation laws induced from the Lyapunov stability in the following subsection. For this end, the weighting vector A is defined as

$$\begin{aligned}A=[&a_1\ a_2\ \cdots\ a_{N_i}\ m_{11}\ m_{12}\ \cdots\ m_{1N_i}\ m_{21}\ \cdots\ m_{2N_i}\ \cdots\ m_{N_wN_i}\\ &d_{11}\ d_{12}\ \cdots\ d_{1N_i}\ d_{21}\ \cdots\ d_{2N_i}\ \cdots\ d_{N_wN_i}\ \theta_{11}\ \theta_{12}\ \cdots\ \theta_{1N_i}\\ &\theta_{21}\ \cdots\ \theta_{2N_i}\ \cdots\ \theta_{N_wN_i}\ w_1\ \cdots\ w_{N_w}]^T.\end{aligned} \tag{9}$$

III. Adaptive Backstepping Control System Using SRWNN

The dynamics (2) and (3) are rewritten by using state variables $x_1=\psi$ and $x_2=r$ as follows:

$$\dot{x}_1 = x_2 \tag{10}$$

$$\begin{aligned}\dot{x}_2 &= \ddot{\psi} = \dot{r}\\ &= F + B\delta_r + d_r\\ &= \bar{F} + \bar{B}\delta_r + \Omega(x_1, x_2, \delta_r).\end{aligned} \tag{11}$$

The control objective is to design an adaptive backstepping control system using SRWNN for the state vector x_1 to track the reference trajectory ψ_d. Here, it is assumed that $\psi_d, \dot{\psi}_d, \ddot{\psi}_d$ are the bounded functions of the time. Now we design the adaptive controller using SRWNN via the backstepping design technique[18] shown in Fig. 3 step by step.

Step 1: Design the virtual controller x_2:

For the tracking control of the state x_1, define the tracking error as

$$E_1(t)=x_1(t)-\psi_d(t). \tag{12}$$

And its derivative is

$$\dot{E}_1(t)=\dot{x}_1(t)-\dot{\psi}_d(t)=v(t)-\dot{\psi}_d(t), \tag{13}$$

where, $v(t)=\dot{x}_1(t)$ is called the virtual control.

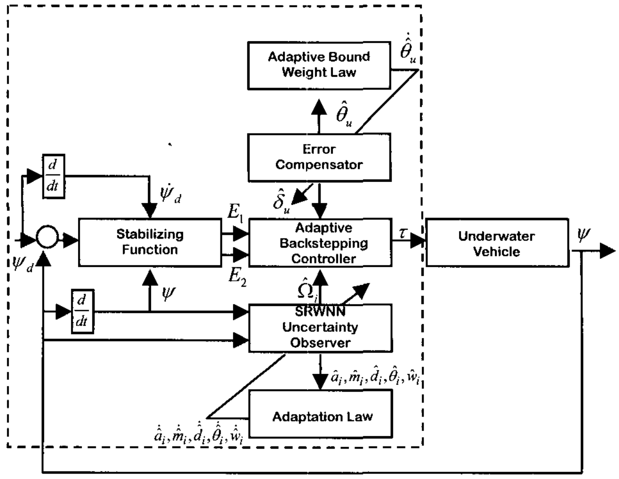


그림 3. 제안된 제어 시스템의 구성도.

Fig. 3. Block diagram of the proposed control system.

Then, the stabilizing function $s(t)$ is defined as

$$s(t) = -K_1E_1(t) + \dot{\psi}_d(t), \tag{14}$$

where K_1 is a positive definite diagonal matrix.

The first Lyapunov function $V_1(t)$ is chosen as

$$V_1(t) = \frac{1}{2}E_1^T E_1. \tag{15}$$

Then, its derivative is as follows:

$$\begin{aligned}\dot{V}_1(t) &= E_1^T \dot{E}_1\\ &= E_1^T(\dot{x}_1(t) - \dot{\psi}_d(t))\\ &= E_1^T(v(t) - s(t) - K_1E_1(t)).\end{aligned} \tag{16}$$

Here, if the virtual control $v(t)$ is chosen as the stabilizing function $s(t)$, the Lyapunov stability condition $\dot{V}_1(t) < 0$ is satisfied. Thus, the asymptotic convergence of the position tracking error $E_1(t)$ can be guaranteed.

Step 2: Design the actual controller τ using SRWNN:

In order to design the actual controller τ, we define E_2 as $E_2 = v(t) - s(t)$. And then, its derivative of the E_2 is expressed as follows

$$\begin{aligned}\dot{E}_2 &= \dot{v}(t) - \dot{s}(t)\\ &= \dot{x}_2(t) + K_1\dot{E}_1(t) - \ddot{\psi}_d(t)\\ &= \bar{F} + \bar{B}\delta_r + \Omega(x_1, x_2, \delta_r) + K_1\dot{E}_1(t) - \ddot{\psi}_d(t),\end{aligned} \tag{17}$$

where, $\Omega(q, \dot{q}, \delta_r)$ is the uncertainty and external disturbance term, δ_r is a function of x_1, x_2 and $\Psi_d = (\psi_d, \dot{\psi}_d, \ddot{\psi}_d)$ which denotes the reference position, velocity and acceleration. Accordingly, the uncertainty term can be represented as $\Omega(x_1, x_2, \delta_r) = \Omega(x_1, x_2, \Psi_d)$. To design the backstepping control system, the Lyapunov function is define as

$$V_2(E_1(t), E_2(t)) = V_1 + \frac{1}{2}E_2^T E_2. \tag{18}$$

And its derivative can be derived as follows:

$$\begin{aligned} \dot{V}_2 &= \dot{V}_1 + E_2^T \dot{E}_2 \\ &= E_1^T (E_2 - K_1 E_1(t)) \\ &\quad + E_2^T \left[\bar{F} + \bar{B}\delta_r + \Omega(x_1, x_2, \delta_r) + K_1 \dot{E}_1(t) - \ddot{\psi}_d(t) \right] \end{aligned} \tag{19}$$

From (20), the backstepping control law δ_r is designed as

$$\begin{aligned} \delta_r = \bar{B}^{-1} \{ & -\bar{F} - \Omega(x_1, x_2, \delta_r) - K_1 \dot{E}_1(t) \\ & + \ddot{\psi}_d(t) - K_2 E_2(t) - E_1(t) \} \end{aligned} \tag{20}$$

where, K_2 is a positive definite diagonal matrix form (19), the backstepping control system is the asymptotic stable. However, since the uncertainty and external disturbance term is the unknown value, δ_r cannot be evaluated. According to the powerful approximation ability[16], in this paper the SRWNN is used to observe the nonlinear uncertainty and external disturbance term $\Omega(x_1, x_2, \delta_r)$ to a sufficient degree of accuracy. The inputs of the SRWNN are the states x_1 and x_2, and its output is $\hat{\Omega}$. Thus the uncertainty and external disturbance term $\Omega(x_1, x_2, \delta_r)$ can be described by the optimal SRWNN plus a reconstruction error vector ε_1 as follows:

$$\begin{aligned} \Omega(x) &= \Omega^*(x \mid A^*) + \varepsilon_1 \\ &= \hat{\Omega}(x \mid \hat{A}) + \left[\Omega^*(x \mid A^*) - \hat{\Omega}(x \mid \hat{A}) \right] + \varepsilon_1, \end{aligned} \tag{21}$$

where, $x = (x_1, x_2)$, $\hat{A} = diag\left[\hat{A}_1, \hat{A}_2, \ldots, \hat{A}_n \right]$; $\hat{A}_i \in R^{(3N_w N_i + N_w + N_i) \times 1} (i = 1, 2, \ldots, n)$ is the estimated vector of weighting vector A of the SRWNN defined in Section II, and A^* is the optimal weighting matrix that achieves the minimum reconstruction error. Then, taking Taylor series expansion of $\Omega^*(x \mid A^*)$ around A and substituting it into (21), (21) can be represented by[19]

$$\begin{aligned} \Omega(x) &= \Omega^*(x \mid A^*) + \varepsilon_1 \\ &= \hat{\Omega}(x \mid \hat{A}) + \tilde{A}^T \left[\frac{\partial \hat{\Omega}(x \mid \hat{A})}{\partial \hat{A}} \right] + \alpha, \end{aligned} \tag{22}$$

where $\tilde{A}(t) = A^* - \hat{A}(t)$ and $\alpha(t, x) = H(A^*, \hat{A}) + \varepsilon_1$. Here, $H(A^*, \hat{A})$ is high order term.

Assumption 4: It is assumed that the reconstruction error term plus high-order term is bounded as

$$\|\alpha(t, x)\| \le \delta_u = \theta_u^T \Lambda_u(t, x), \tag{23}$$

where $\theta_u \in R^3$ is an unknown vector and $\Lambda_u(t, x) = \left[1, \|x_1(t)\|, \|x_2(t)\| \right]^T$ is a chosen regressor vector.

From the boundedness of $\alpha(t, x)$, it can be easily shown that Assumption 4 is reasonable. The reconstruction error term ε_1 is bounded by a positive function since it can be reduced by increasing the number of the hidden nodes of the SRWNN. Also, a high-order term H is bounded by a positive constant[19]. Since the weights of the SRWNN are trained by the adaptation law induced from Theorem 1, $\hat{A} \to A^*$ as $t \to \infty$. Thus, it is reasonable that the size of high order terms is bounded by the positive constant. Therefore, based on the boundedness of a high-order term H and the reconstruction error term ε_1, α is a function of X and bounded. Accordingly, the regressor vector can be chosen as the above equation. Then, we propose the adaptive backstepping control law using SRWNN as follows:

$$\begin{aligned} \tau(\delta_r) = B^{-1} \Bigg[& -F - \hat{\Omega}(x \mid \hat{A}) - \hat{\delta}_u \frac{E_2(t)}{\|E_2(t)\| + \beta} \\ & - K_1 \dot{E}_1(t) + \ddot{\psi}_d(t) - K_2 E_2(t) - E_1(t) \Bigg], \end{aligned} \tag{24}$$

Remark 1: SMC boundary layer technique is used to eliminate the chattering in the control input by adding β to the actual control input δ_r.

Theorem 1: Assume that the steering model of an AUV (2) and (3) with unknown model uncertainties is controlled by the SRWNN based backstepping control law (24). Then, if the tuning parameters of the SRWNN and the error compensator $\hat{\delta}_u$ are trained by the following adaptation rules:

$$\dot{\hat{A}}_i = \lambda_{1,i} \left[\frac{\partial \hat{\Omega}_i(x \mid \hat{A}_i)}{\partial \hat{A}_i} \right] E_{2,i}(t) \tag{25}$$

$$\dot{\hat{\theta}}_u = \|E_2(t)\| \lambda_2 \Lambda_u(t, x) \tag{26}$$

where, $i = 1, \ldots, n$, $\lambda_1 = diag\left[\lambda_{1,1}, \lambda_{1,2}, \ldots, \lambda_{1,n} \right]$; $\lambda_{1,i} \in R^{(3N_w N_i + N_w + N_i) \times 1}$ and $\lambda_2 = diag\left[\lambda_{2,1}, \lambda_{2,2}, \lambda_{2,3} \right]$; are positive tuning gain matrices, the asymptotic stability of the SRWNN based backstepping system can be guaranteed.

Proof: A Lyapunov candidate is chosen as

$$V_3 = V_2 + \frac{1}{2} tr(\tilde{A}^T \lambda_1^{-1} \tilde{A}) + \frac{1}{2} \tilde{\theta}_u^T \lambda_2^{-1} \tilde{\theta}_u^T \tag{27}$$

where, $\tilde{\theta}_u(t) = \hat{\theta}_u(t) - \theta_u^*$ and $tr(\cdot)$ denote the trace of a matrix. Here, $\hat{\theta}_u$ is the estimated parameters of δ_u, which is used to compensate the observed error induced by the SRWNN uncertainty observer. Differentiating the Lyapunov function (27) and using (22) and (24), we obtain that

$$\begin{aligned} \dot{V}_3 &= \dot{V}_2 - tr(\tilde{A}^T \lambda_1^{-1} \dot{\hat{A}}) + \tilde{\theta}_u^T \lambda_2^{-1} \dot{\hat{\theta}}_u \\ &= -E_1^T(t) K_1 E_1(t) - E_2^T(t) K_2 E_2(t) \\ &\quad + E_2^T(t) \tilde{A}^T \left[\frac{\partial \hat{\Omega}(x \mid \hat{A})}{\partial \hat{A}} \right] + E_2^T(t) \alpha \\ &\quad - \hat{\delta}_u \|E_2(t)\| - tr(\tilde{A}^T \lambda_1^{-1} \dot{\hat{A}}) + \tilde{\theta}_u^T \lambda_2^{-1} \dot{\hat{\theta}}_u \end{aligned} \tag{28}$$

By applying (23), we obtain that

$$\dot{V}_3 \le -E_1^T(t)K_1E_1(t) - E_2^T(t)K_2E_2(t) - tr\left\{\tilde{A}^T\left(\lambda_1^{-1}\dot{\hat{A}} - \left[\frac{\partial\hat{\Omega}(x\,|\,\hat{A})}{\partial\hat{A}}\right]E_2^T(t)\right)\right\} - \|E_2(t)\|\delta_u + \tilde{\theta}_u^T\lambda_2^{-1}\dot{\hat{\theta}}_u \tag{29}$$

where $\tilde{\delta}_u = \hat{\delta}_u - \delta_u$ and $\tilde{\delta}_u = \theta_u^T\Lambda_u$. Thus,

$$\dot{V}_3 \le -E_1^T(t)K_1E_1(t) - E_2^T(t)K_2E_2(t) - tr\left\{\tilde{A}^T\left(\lambda_1^{-1}\dot{\hat{A}} - \left[\frac{\partial\hat{\Omega}(x\,|\,\hat{A})}{\partial\hat{A}}\right]E_2^T(t)\right)\right\} - \tilde{\theta}_u^T(\Lambda_u\|E_2(t)\| - \lambda_2^{-1}\dot{\hat{\theta}}_u) \tag{30}$$

Then, if the adaptation laws (25) and (26) are applied to the above equation, we can obtain that

$$\dot{V}_3 \le -E_1^T(t)K_1E_1(t) - E_2^T(t)K_2E_2(t) \le -\Gamma(t) \le 0 \tag{31}$$

Because $\dot{V}_3(E_1(t), E_2(t), \tilde{A}, \tilde{\theta}_u) \le 0, \dot{V}_3$ is negative semidefinite (i.e., $V_3(E_1(t), E_2(t), \tilde{A}, \tilde{\theta}_u) \le V_3(E_1(0), E_2(0), \tilde{A}, \tilde{\theta}_u)$, which implies $E_1(t), E_2(t), \tilde{A}$, and $\tilde{\theta}_u$ are bounded. We can obtain that $\Gamma(t) \le -\dot{V}_3$ and integrating $\Gamma(t)$ with respect to time,

$$\int_0^t \Gamma(\tau)d\tau \le V_3(E_1(0), E_2(0), \tilde{A}, \tilde{\theta}_u) - V_3(E_1(t), E_2(t), \tilde{A}, \tilde{\theta}_u) \tag{32}$$

Because $V_3(E_1(0), E_2(0), \tilde{A}, \tilde{\theta}_u)$ is bounded and $V_3(E_1(t), E_2(t), \tilde{A}, \tilde{\theta}_u)$ is non-increasing and bounded, we obtain the following result:

$$\lim_{t\to\infty}\int_0^t \Gamma(\tau)d\tau < \infty \tag{33}$$

It can be concluded that $\dot{\Gamma}(t)$ is bounded, and $\Gamma(t)$ is uniformly continuous. By using Barbalat's Lemma[20], $\lim_{t\to\infty}\Gamma(t) = 0$. That is, $E_1(t)$ and $E_2(t)$ will converge to zero as $t \to \infty$. Therefore, the asymptotic stability of our control system is satisfied.

IV. Simulations

1. Proposed adaptive backstepping controller design

In this section, we validate the proposed control laws expressed as (13) and (25) by applying it to a 6 DOF nonlinear dynamical model of REMUS AUV, which is under development in WHOI, U.S.A. The steering behavior of REMUS AUV can be expressed as follows:

$$\dot{\psi} = r$$
$$\dot{r} = F + B\delta_r + d_r$$

In Section 2, while deriving the steering dynamics model of an AUV, we assume that the vehicle's forward speed is constant and the heave and pitch angular velocities are close to zero. Also, the roll dynamics of an AUV is neglected. In this simulation, the unstructured uncertainty and disturbance term is chosen as $d_r = r\sin(5t)$. Also desired trajectory is chosen as $\psi_d = \sin(0.7t) + 2\cos(0.3t)$, and other design parameters are selected as follows:

$$u_0 = 1.54m/s,\ k_1 = 0.5,\ k_2 = 0.3,\ \lambda_1 = 0.001,\ \lambda_2 = 0.01.$$

In the proposed control system, each SRWNN consists of the very simple structure: two inputs, two mother wavelet, one product node and one output. The initial values of weights of the SRWNNs are chosen randomly in the range of [-1 1], but $d_{jk} > 0$. And also, the initial values of θ_{jk} are given by 0. That is, there are no feedback units initially. The inaccurate initial tuning parameters of the SRWNNs are trained optimally via on-line parameter tuning methodology.

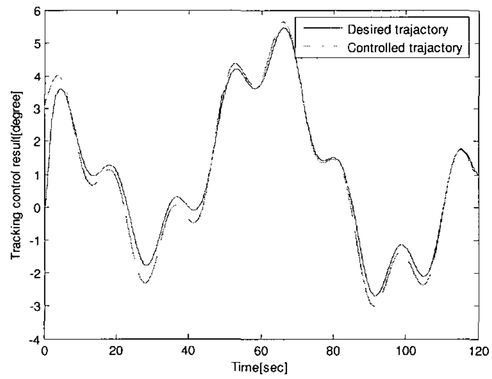
2. Simulation results

The main focus of this paper is on the robustness and the good performance of the proposed SRWNN based adaptive controller for the nonlinear steering control of an AUV. In order to confirm

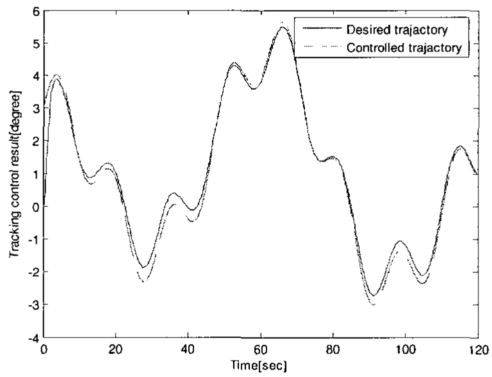
표 1. 모의실험 결과.

Table 1. Simulation results.

Number of wavelet function		1
Sampling time		0.1
β (width of boundary layer)		0.7
Control result(MSE)	with disturbance	0.0071
	without disturbance	0.0079



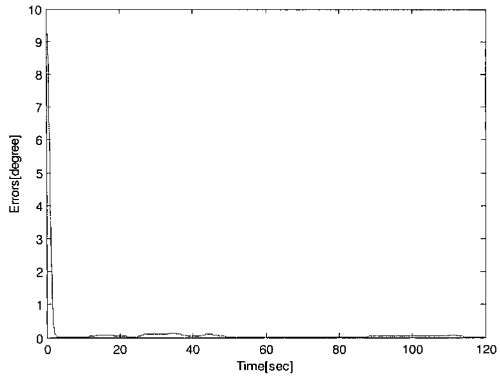
(a) Without external disturbance



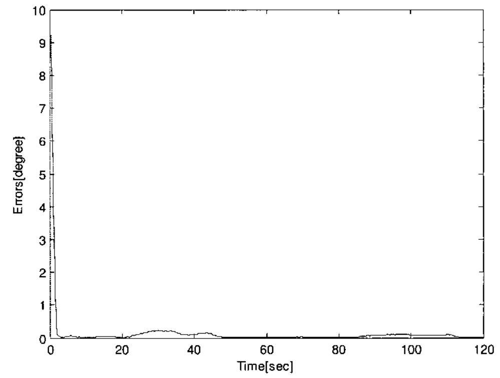
(b) With external disturbance

그림 4. AUV 의 조정 모델을 위한 추종 제어 결과.

Fig. 4. Tracking control results for the steering model of an AUV.



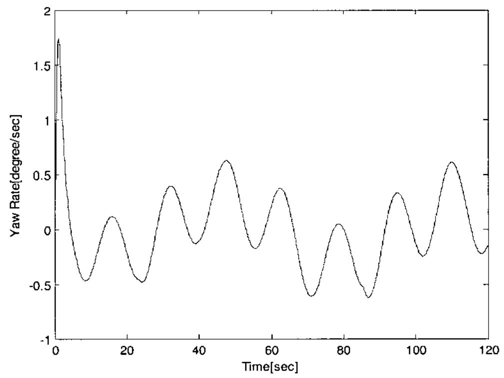
(a) Without external disturbance



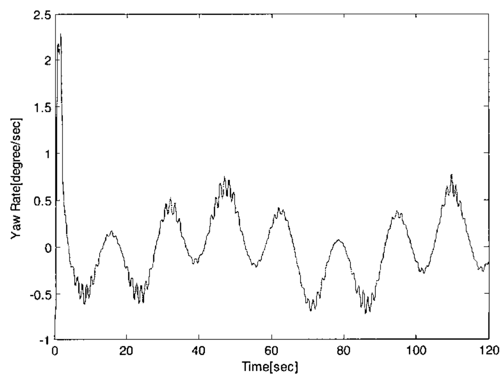
(b) With external disturbance

그림 5. 추종 에러.

Fig. 5. Tracking errors.



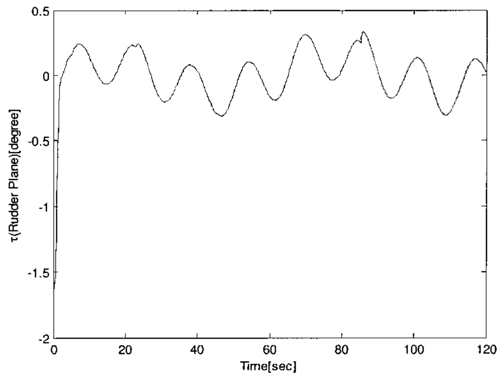
(a) Without external disturbance



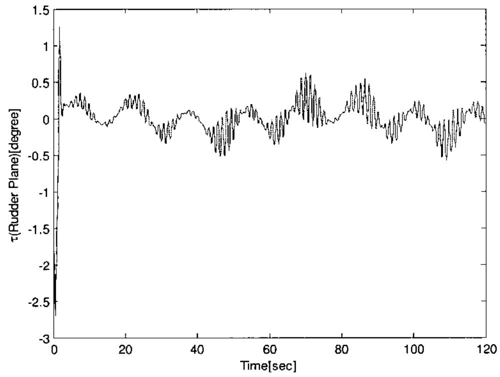
(b) With external disturbance

그림 6. 편주율.

Fig. 6. Yaw rate.



(a) Without external disturbance



(b) With external disturbance

그림 7. 제어 입력(키 평면 각).

Fig. 7. Control input(rudder plane angle).

the advantage of the proposed control scheme, we compare the control performance with the case where the disturbance terms, such as d_r is not considered. Simulation results are shown in Table 1 and depicted in Figs. 4-7.

Fig. 4(a) shows the tracking control results of the proposed control method when the external disturbance is not considered. And Fig. 4(b) shows the tracking control results of the proposed control method when the external disturbance is considered. From comparison of these results, we can confirm that the proposed control has the excellent tracking performance even though there exists disturbance, and the SRWNN observer has the certain satisfactory approximation capacities under the above simulation conditions. Figs. 5 and 6 show the tracking errors and the yaw rate, respectively. According to the physical property of an AUV, the fin angle can not be taken as any free value. If the fin angle exceeds the certain bound, then the fin lift force may be saturated [14]. In this simulation, we saturate the rudder plane angle as-0.5° $\leq \delta_r \leq$ 0.5° and the corresponding control input(rudder plane angle) is shown in the Fig. 7. As a result, the proposed method can overcome unknown model uncertainties resulting from the steering model of an AUV dynamics with external disturbances.

V. Conclusion

We have presented an SRWNN based adaptive backstepping controller for the steering control of AUV system with model uncertainties. The dynamics of AUV have heavy nonlinearities and hydrodynamics coefficients, which are difficult to be accurately estimated priori owing to variations of these coefficients with different operating ocean environment. In this thesis, it was assumed that the unstructured uncertainties in the AUV's dynamics were unbounded and also added external disturbance was added. The SRWNN having the simple structure was employed as the uncertainty observer and the error compensator was used to compensate the observed error induced by the SRWNN uncertainty observer. The adaptation laws for training weights of SRWNNs and error compensators were induced from the Lyapunov stability theory, which were applied to guarantee the asymptotic stability of the proposed controller. Through computer simulations, we confirmed that the control signals are obtained by minimizing the difference between the reference track and the pose of AUV system whether it had disturbance or not. As a result, we verified that the proposed controller has the robustness against disturbance. Finally, we showed that the SRWNN based adaptive backstepping controller can be applied to the robust control of AUV steering system.

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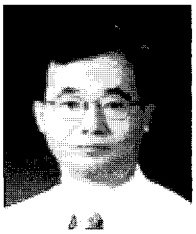

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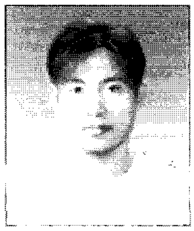

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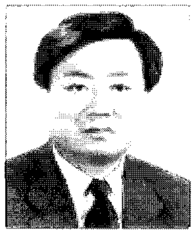

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