이족 로봇의 안정한 걸음새를 위한 자기 회귀 웨이블릿 신경 회로망을 이용한 적응 백스테핑 제어

Adaptive Backstepping Control Using Self Recurrent Wavelet Neural Network for Stable Walking of the Biped Robots

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Abstract : This paper presents the robust control method using a self recurrent wavelet neural network (SRWNN) via adaptive backstepping design technique for stable walking of biped robots with unknown model uncertainties. The SRWNN, which has the properties such as fast convergence and simple structure, is used as the uncertainty observer of the biped robots. The adaptation laws for weights of the SRWNN and reconstruction error compensator are induced from the Lyapunov stability theorem, which are used for on-line controlling biped robots. Computer simulations of a five-link biped robot with unknown model uncertainties verify the validity of the proposed control system.

Keywords : adaptive backstepping control, self recurrent wavelet neural network, biped robot

I. Introduction

The biped robot control has been received increased attention due to their human-like mobility moving on steep stairs, obstructed environments. This mobility enables the biped robots to perform the dangerous works instead of humans. Thus, the stable walking control of the biped robots is a fundamentally hot issue and has been studied by many researchers[1-3]. However, the inherent instability caused by two legged locomotion makes difficult control the biped robots. Besides, unlike the robot manipulator, the biped robot has an uncontrollable degree of freedom in the biped robot dynamics playing a dominant role in the stability of their locomotion. In recent year, various control techniques such as computed torque control[1], sliding model control[2], active force control[3] are used for controlling the biped robot. Especially, [1] has contributed for the dynamic modeling and robust control of the five-link biped robot. However, these works have a problem that the bounds of the uncertainties and disturbances must be known for the design of the control law. Actually, in real applications, the parameter variations of the system are difficult to predict, and the external disturbances changed according to the environment are also difficult to know.

The adaptive backstepping control is a systematic and recursive design methodology for nonlinear feedback control. Unlike the feedback linearization method having the problems such as the precise model and the cancellation of useful nonlinear terms, the adaptive backstepping design offers a choice of design tools for accommodation of uncertainties and nonlinearities, and can avoid wasteful cancellations[4,5]. The key idea of the adaptive backstepping design is to select recursively some appropriate state variables as virtual inputs for lower dimension subsystems of the overall system and the Lyapunov functions are designed for each stable virtual controller[4]. Therefore, the finally designed adaptive backstepping control law can guarantee the stability of total control system.

On the other hand, self recurrent wavelet neural network (SRWNN)[6,7] was proposed to compensate the disadvantage of a wavelet neural network (WNN)[8] such as the static mapping. In this paper, the adaptive backstepping control method using the SRWNN having the powerful dynamic mapping ability and simple structure are proposed for stable walking of biped robots. In our control system, the SRWNN is employed as the uncertainty observer in the adaptive backstepping controller and the error compensator is also used to reduce the approximation error of SRWNN. The adaptation laws for weights of the uncertainty observer and the error compensator are induced from the Lyapunov stability theorem, which are used to guarantee the asymptotic stability. Finally, the simulation results for the five-link biped robot are provided to demonstrate the effectiveness of the proposed control scheme.

II. Preliminaries

1. The biped robot model with uncertainties

The motion of biped robots are achieved via various

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phased movements such as the single leg support phase, the double leg support phase, and the biped in the air phase[1-3]. In this paper, the biped dynamic model is simplified by only considering the single support phase. The dynamics of the biped robot with model uncertainties in single support phase can be expressed in the following Lagrange form[10]:

$$M(q)\ddot{q} + C(q,\dot{q}) + G(q) + F(\dot{q}) + \Xi(q,\dot{q},\tau) = \tau \quad (1)$$

where

$$\Xi(q,\dot{q},\tau) = -M(q)\overline{M}^{-1}(q)\{\tau - \tau_d - \overline{C}(q,\dot{q}) - \overline{G}(q) - \overline{F}(\dot{q})\} + \{\tau - C(q,\dot{q}) - G(q) - F(\dot{q})\}$$

denotes the uncertainty of the robot system, and $M(q) \in \mathbb{R}^{n\times n}$ is the inertia matrix, $C(q,\dot{q}) \in \mathbb{R}^n$ denotes the Coriolis and centrifugal torques, $G(q) \in \mathbb{R}^n$ is the gravity vector, $F(\dot{q}) \in \mathbb{R}^n$ represents the friction term, and the control input torque is $\tau \in \mathbb{R}^n$. Also, $\overline{M}(q)$, $\overline{C}(q,\dot{q})$, $\overline{G}(q)$, and $\overline{F}(\dot{q})$ are the actual values with uncertainties in the nominal values $M(q)$, $C(q,\dot{q})$, $G(q)$, and $F(\dot{q})$, respectively. τ_d is the external disturbance. In this paper, it is assumed that the nominal values are only known values for a given robot system. That is, suppose that the actual values $\overline{M}(q)$, $\overline{C}(q,\dot{q})$, $\overline{G}(q)$, and $\overline{F}(\dot{q})$ and the external disturbance τ_d are the unknown values. Accordingly, the uncertainty term $\Xi(q,\dot{q},\tau)$ cannot be computed.

2. SRWNN structure

A schematic diagram of the SRWNN structure shown in Fig. 1 has N_i inputs, one output, and $N_i \times N_w$ mother wavelets[6,7]. The SRWNN structure consists of four 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[8] as a mother wavelet function. The nodes in a product layer are given by the product of the mother wavelets as follows:

$$\Phi_j(x) = \prod_{k=1}^{N_i} \phi(z_{jk}), \quad \text{whit } z_{jk} = \frac{u_{jk} - m_{jk}}{d_{jk}}, \qquad (2)$$

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

$$u_{jk} = x_k + \phi_{jk} z^{-1} \cdot \theta_{jk}, \qquad (3)$$

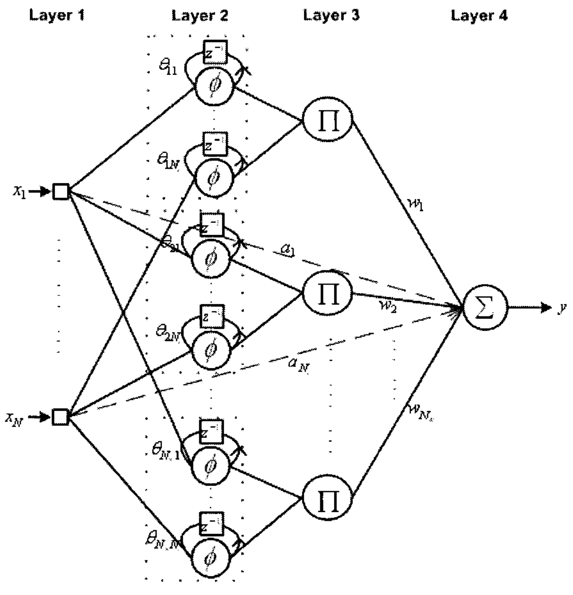


Fig. 1. SRWNN structure.

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 of the network. That is, the current dynamics of the system is conserved for the next sample step. Here, θ_{jk} is a factor to represent the rate of information storage. 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:

$$y = \sum_{j=1}^{N_w} w_j \Phi_j(x) + \sum_{k=1}^{N_i} a_k x_k, \qquad (4)$$

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 section. To this end, we define the weighting vector as

$$A = [a_1 \cdots a_{N_i}\ m_{11} \cdots m_{N_w 1}\ m_{12} \cdots m_{N_w 2} \cdots\cdots m_{N_w N_i}\ d_{11} \cdots d_{N_w 1}\ d_{12} \cdots d_{N_w 2} \cdots\cdots d_{N_w N_i}\ \theta_{11} \cdots \theta_{N_w 1}\ \theta_{12} \cdots \theta_{N_w 2} \cdots\cdots \theta_{N_w N_i}\ w_1 \cdots w_{N_w}]^T$$

where $A \in \mathbb{R}^{(3N_w N_i + N_w + N_i)\times 1}$.

III. Adaptive Backstepping Control System using SRWNN

The dynamics (1) is rewritten by using state variables $X_1 = q$ and $X_2 = \dot{q}$ as follows:

$$\begin{aligned} \dot{X}_1 &= X_2 \\ \dot{X}_2 &= M^{-1}(X_1)\{\tau - C(X_1, X_2) - G(X_1) \\ &\quad - F(X_2) - \Xi(X_1, X_2, \tau)\}. \end{aligned} \tag{5}$$

The control objective is to design an adaptive backstepping control system based on SRWNN for the state vector X_1 to track the reference trajectory vector q_d. Here, it is assumed that q_d, $\dot{q}_d$, and $\ddot{q}_d$ are the bounded functions of the time. We now design the adaptive controller using SRWNN via backstepping design technique[4] shown in Fig. 2 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

$$Z_1(t) = X_1(t) - q_d(t), \tag{6}$$

and its derivative is

$$\dot{Z}_1(t) = \dot{X}_1(t) - \dot{q}_d(t) = \boldsymbol{v}(t) - \dot{q}_d(t), \tag{7}$$

where $\boldsymbol{v}(t) = \dot{X}_1(t)$ is called the virtual control. Then, the stabilizing function $\boldsymbol{s}(t)$ is defined as

$$\boldsymbol{s}(t) = -K_1 Z_1(t) + \dot{q}_d(t), \tag{8}$$

when K_1 is a positive definite diagonal matrix.
The first Lyapunov function $V_1(t)$ is chosen as

$$V_1(t) = \frac{1}{2} Z_1^T Z_1. \tag{9}$$

Then, its derivative is

$$\begin{aligned} \dot{V}(t) &= Z_1^T \dot{Z}_1 \\ &= Z_1^T(\dot{X}_1(t) - \dot{q}_d(t)) \\ &= Z_1^T(\boldsymbol{v}(t) - \boldsymbol{s}(t) - K_1 Z_1(t)). \end{aligned} \tag{10}$$

Here, if the virtual control $\boldsymbol{v}(t)$ is chosen as the stabilizing function $\boldsymbol{s}(t)$, the Lyapunov stability condition $\dot{V}_1(t) < 0$ is satisfied. Thus, the asymptotic convergence of the position tracking error $Z_1(t)$ can be guaranteed.

Step 2: Design the actual controller τ using SRWNN.

To design the actual controller τ, we define Z_2 as $Z_2 = \boldsymbol{v}(t) - \boldsymbol{s}(t)$. And then, its derivative of the Z_2 is expressed as

$$\begin{aligned} \dot{Z}_2 &= \dot{\boldsymbol{v}}(t) - \dot{\boldsymbol{s}}(t) \\ &= \dot{X}_2(t) + K_1 \dot{Z}_1(t) - \ddot{q}_d(t) \\ &= M^{-1}(X_1)\{\tau - C(X_1, X_2) - G(X_1) \\ &\quad - F(X_2)\} + \Gamma(X_1, X_2, \tau) + K_1 \dot{Z}_1(t) - \ddot{q}_d(t), \end{aligned} \tag{11}$$

where, $\Gamma(X_1, X_2, \tau) \equiv -M^{-1}(X_1)\Xi(X_1, X_2, \tau)$ is the uncertainty term, τ is a function of X_1, X_2, and $Q_d = (q_d, \dot{q}_d, \ddot{q}_d)$ which denotes the reference position, velocity, and acceleration. Accordingly, the uncertainty term can be represented as $\Gamma(X_1, X_2, \tau) = \Gamma(X_1, X_2, Q_d)$.

To design the backstepping control system, the Lyapunov function is defined as

$$V_2(Z_1(t), Z_2(t)) = V_1 + \frac{1}{2} Z_2^T Z_2 \tag{12}$$

And its derivative can be derived as follows:

$$\begin{aligned} \dot{V}_2 &= \dot{V}_1 + Z_2^T \dot{Z}_2 \\ &= Z_1^T(Z_2 - K_1 Z_1(t)) + Z_2^T [M^{-1}(X_1) \\ &\quad \{\tau - C(X_1, X_2) - G(X_1) \quad - F(X_2)\} \\ &\quad + \Gamma(X_1, X_2, Q_d) + K_1 \dot{Z}_1(t) - \ddot{q}_d(t)] \end{aligned} \tag{13}$$

From (13), if the backstepping control law τ is designed as

$$\begin{aligned} \tau &= C(X_1, X_2) + G(X_1) + F(X_2) + M(X_1) \\ &\quad [-\Gamma(X_1, X_2, Q_d) - K_1 \dot{Z}_1(t) + \ddot{q}_d(t) - K_2 Z_2(t) \\ &\quad - Z_1(t)], \end{aligned} \tag{14}$$

where K_2 is a positive definite diagonal matrix, from (13), the backstepping control system is the asymptotic stable.
However, since the uncertainty term $\Gamma(X_1, X_2, Q_d)$ is the unknown value, τ cannot be evaluated. According to the powerful approximation ability[6], we employ the SRWNN to observe the nonlinear uncertainty term $\Gamma(X_1, X_2, Q_d)$ to a sufficient degree of accuracy. The inputs of the SRWNN are the states X_1 and X_2, and its output is $\hat{\Gamma}$. Thus the uncertainty term $\Gamma(X_1, X_2, Q_d)$ can be described by the optimal SRWNN plus a reconstruction error vector ϵ_1 as follows:

$$\begin{aligned} \Gamma(X) &= \Gamma^*(X|A^*) + \epsilon_1 \\ &= \hat{\Gamma}(X|\hat{A}) + [\Gamma^*(X|A^*) - \hat{\Gamma}(X|\hat{A})] + \epsilon_1, \end{aligned} \tag{15}$$

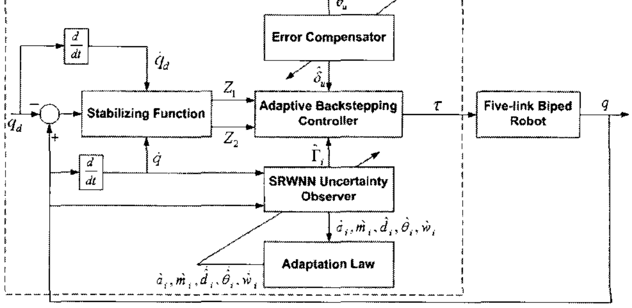


Fig. 2. Block diagram of the proposed control system.

where $X=(X_1,X_2)$, $\hat{A}=diag[\hat{A}_1,\hat{A}_2,...,\hat{A}_n]$; $\hat{A}_i\in\mathbb{R}^{(3N_wN_i+N_w+N_i)\times 1}(i=1,2,...,n)$ is the estimated vector of weighting vector A of the SRWNN defined in Section 2.2, and A^* is the optimal weighting matrix that achieves the minimum reconstruction error. Then, taking the Taylor series expansion of $\Gamma^*(X|A^*)$ around $\hat{A}$ and substituting it into (15), (15) can be represented by[9]

$$\begin{aligned}\Gamma(X)&=\Gamma^*(X|A^*)+\epsilon_1\\&=\hat{\Gamma}(X|\hat{A})+\tilde{A}^T\left[\frac{\partial\hat{\Gamma}(X|\hat{A})}{\partial\hat{A}}\right]+\alpha,\end{aligned}\tag{16}$$

where $\tilde{A}(t)=A^*-\hat{A}(t)$, and $\alpha(t,X)=H(A^*,\hat{A})+\epsilon_1$. Here, $H(A^*,\hat{A})$ is a high-order term.

Assumption 1 [13]: It is assumed that the reconstruction error term plus high-order term is bounded as

$$\|\alpha(t,X)\|\le\delta_u=\theta_u^T\Lambda_u(t,X)\tag{17}$$

where $\theta_u\in\mathbb{R}^3$ is an unknown vector and $\Lambda_u(t,X)=[1,\|X_1(t)\|,\|X_2(t)\|]^T$ is a chosen regressor vector.

From the boundedness of $\alpha(t,X)$, it can be easily shown that Assumption 1 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[9]. Since the weights of the SRWNN are trained by the adaptation law induced from Theorem 1, $\hat{A}->A^*$ as $t->\infty$. Thus, it is resonable that the size of the 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, the 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:

$$\begin{aligned}\tau=&C(X_1,X_2)+G(X_1)+F(X_2)+M(X_1)[-\hat{\Gamma}(X|\hat{A})\\&-\hat{\delta}_u\frac{Z_2(t)}{\|Z_2(t)\|}-K_1\dot{Z}_1(t)+\ddot{q}_d(t)-K_2Z_2(t)-Z_1(t)],\end{aligned}\tag{18}$$

Theorem 1: Assume that the robotic system (1) with unknown model uncertainties is controlled by the SRWNN based backstepping control law (18). Then if the tuning parameters of the SRWNN and the error compensator $\hat{\delta}_u$ are trained by the following adaptation rules:

$$\dot{\hat{A}}_i=\lambda_{1,i}\left[\frac{\partial\hat{\Gamma}_i(X_i|\hat{A}_i)}{\partial\hat{A}_i}\right]Z_{2,i}(t)\tag{19}$$

$$\dot{\hat{\theta}}_u=\|Z_2(t)\|\lambda_2\Lambda_u(t,X)\tag{20}$$

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

Proof: A Lynapunov candidate is chosen as

$$V_3=V_2+\frac{1}{2}tr(\tilde{A}^T\lambda_1^{-1}\tilde{A})+\frac{1}{2}\tilde{\theta}_u^T\lambda_2^{-1}\tilde{\theta}_u.\tag{21}$$

where $\tilde{\theta}_u(t)=\hat{\theta}_u(t)-\theta_u^*$, and $tr(\cdot)$ denotes 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 (21) and using (16) and (18), we obtain

$$\begin{aligned}\dot{V}_3=&\dot{V}_2-tr(\tilde{A}^T\lambda_1^{-1}\dot{\hat{A}})+\tilde{\theta}_u^T\lambda_2^{-1}\dot{\hat{\theta}}_u\\=&-Z_1^T(t)K_1Z_1(t)-Z_2^T(t)K_2Z_2(t)\\&+Z_2^T(t)\tilde{A}^T\left[\frac{\partial\hat{\Gamma}(X|\hat{A})}{\partial\hat{A}}\right]+Z_2^T(t)\alpha-\hat{\delta}_u\|Z_2(t)\|\\&-tr(\tilde{A}^T\lambda_1^{-1}\dot{\hat{A}})+\tilde{\theta}_u^T\lambda_2^{-1}\dot{\hat{\theta}}_u.\end{aligned}$$

By applying (17), we obtain

$$\begin{aligned}\dot{V}_3\le&-Z_1^T(t)K_1Z_1(t)-Z_2^T(t)K_2Z_2(t)\\&-tr\left\{\tilde{A}^T\left(\lambda_1^{-1}\dot{\hat{A}}-\left[\frac{\partial\hat{\Gamma}(X|\hat{A})}{\partial\hat{A}}\right]Z_2^T(t)\right)\right\}\\&-\|Z_2(t)\|\tilde{\delta_u}+\tilde{\theta}_u^T\lambda_2^{-1}\dot{\hat{\theta}}_u\end{aligned}$$

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

$$\begin{aligned}\dot{V}_3\le&-Z_1^T(t)K_1Z_1(t)-Z_2^T(t)K_2Z_2(t)\\&-tr\left\{\tilde{A}^T\left(\lambda_1^{-1}\dot{\hat{A}}-\left[\frac{\partial\hat{\Gamma}(X|\hat{A})}{\partial\hat{A}}\right]Z_2^T(t)\right)\right\}\\&-\tilde{\theta}_u^T(\Lambda_u\|Z_2(t)\|-\lambda_2^{-1}\dot{\hat{\theta}}_u).\end{aligned}$$

Then, if the adaptation laws (19) and (20) are applied to the above equation, we can obtain

$$\begin{aligned}\dot{V}_3\le&-Z_1^T(t)K_1Z_1(t)-Z_2^T(t)K_2Z_2(t)\\\le&-\Omega(t)\le 0.\end{aligned}$$

By using Barbalat's Lemma[5], $\lim_{t\to\infty}\Omega(t)=0$. That is, $Z_1(t)$ and $Z_2(t)$ will converge to zero as $t\to\infty$. Therefore, the asymptotic stability of our control system is satisfied.

IV. Simulation

In this simulation, we consider the five-link biped robot shown in Fig. 3. The relative angle of the five-link biped robot is $q=[q_0\ q_1\ q_2\ q_3\ q_4]$. Only four of this five

Table 1. Simulation parameters for the five-link biped robot.

	m_i (Kg)		l_i (m)	d_i (m)	I_i(Kg m) (Moment of inertia)
	Nominal	Actual	Nominal	Nominal	
LINK 1 (Right Leg)	2.23	4.71	0.332	0.189	0.033
LINK 2 (Right Thigh)	5.28	6.82 ×cos(t)	0.302	0.236	0.033
LINK 3 (Torso)	14.79	20.35	0.486	0.282	0.033
LINK 4 (Left Thigh)	5.28	6.73 ×sin(t)	0.302	0.236	0.033
LINK 5 (Left Leg)	2.23	7.84	0.332	0.189	0.033

relative degrees can be controlled directly by the four driving torques at each joints. The angle q_0 at the contact point with the walking surface is controlled indirectly using the gravitational effects. This aspect is the most important characteristics of the locomotion of the biped robot. Accordingly, each of two hip and two keen joints are assumed to be driven only by an independent motor. The motion of the biped robot is assumed to be constrained within the sagittal plane. The biped robot is planned to start walking from the vertical position and walk steadily for several steps on a flat horizontal surface. Actually, the complete motion of the biped robot can be explained by a single support phase, a double support phase, double impact, switching and transformation[11]. Thus, there is a need to switch the dynamic equations and controllers during the iterative computation of the simulation program. However, this method causes the complex programming problems[2]. Accordingly, in this subsection, we apply our control system for stable walking control of the planar five-link biped robot with only a single support phase. The dynamic model and the reference trajectory planned considering only the single support phase proposed in [1,2] are used in this simulation. And to examine the robustness of the proposed control method, we compare the SRWNN based adaptive backstepping control (SRWNNABC) method with the computed torque control (CTC) method.

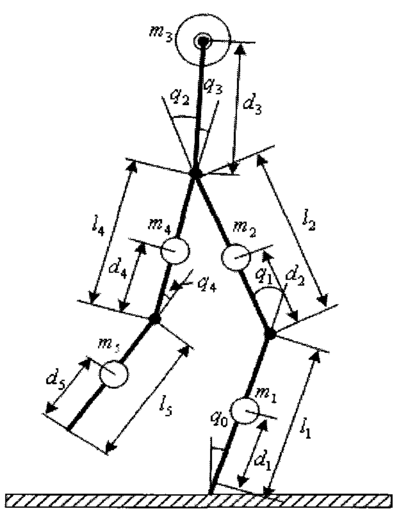


Fig. 3. Five-link biped robot in the sagittal plane.

Since q_0 of the biped robot model is the uncontrollable joint (i. e., τ_1=0), our control law is redefined as follows:

$$\tau = M(X_1)U + C(X_1, X_2) + G(X_1) + F(X_2)$$

where $U \in \mathbb{R}^5$ is the vector with components

$$u_1 = -\frac{1}{M_{11}}\left[\sum_{l=1}^{4}(M_{1l+1} \cdot u_{l+1}) + C_1 + G_1 + F_1\right]$$

$$u_{l+1} = -\hat{\Gamma}_l(X_l | \hat{A}_l) - \hat{\delta}_{u,l}\frac{Z_{2,l}(t)}{\|Z_{2,l}(t)\|} - K_{1,l}\dot{Z}_{1,l}(t) + \ddot{q}_{d,l}(t) - K_{2,l}Z_{2,l}(t) - Z_{1,l}(t)$$

Here, M_{1P} $(P=1,2,\cdots,5)$ denote the components of the first row of matrix $M(X_1)$ and C_1, G_1, and F_1 are the first element of the vectors $C(X_1,X_2)$, $G(X_1)$, and $F(X_2)$, respectively. And to compare the performance of SRWNNABC system and CTC system, we use the error cost function defined as $Cost_e = Z_1(t)^2$, and it is assumed that the same disturbances and uncertainties influence the biped robot system. The initial positions are set to $q_1(0) = q_2(0) = q_3(0) = q_4(0) = 0$ and the link masses m_i s of the biped robot are assumed to be uncertain. Especially, it is assumed that m_2 and m_4 have the time-varying uncertainties and m_5 has about 300% uncertainty of the nominal value. The parameters of the five-link biped robot are shown in Table 1. In addition, the external disturbances given by $\tau_d = [0.4\sin(10t)\ \ 0.3\cos(10t)\ \ 0.7\sin(10t)\ \ 0.6\sin(10t)\ \ 0.3\cos(10t)]^T$ are injected into the biped robot. The parameters of the SRWNNABC system for controlling the states from q_1 to q_4 are chosen as

$$K_1 = diag[200\ 200\ 400\ 300]$$
$$K_2 = diag[100\ 100\ 150\ 150]$$
$$\lambda_1 = diag[0.01\ 0.01\ 0.01\ 0.01]$$
$$\lambda_2 = diag[0.001\ 0.001\ 0.001].$$

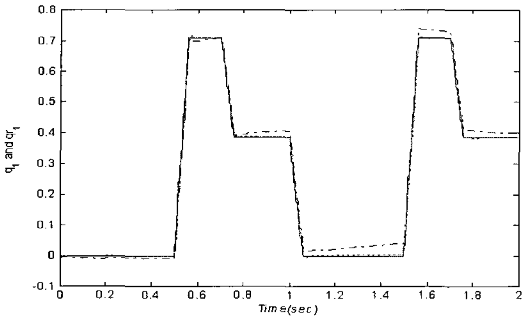
and the parameters of the CTC system are given by

$$K_P = diag[1000\ 1000\ 1000\ 1000]$$
$$K_D = diag[500\ 500\ 500\ 500]$$

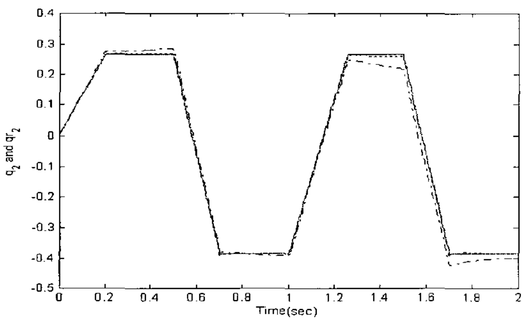
where K_P and K_D are the proportional and derivative gain

Table 2. Comparison of the average tracking errors.

	e_1(rad)	e_2(rad)	e_3(rad)	e_4(rad)
SRWNNABC	0.0019	0.0021	0.0022	0.0018
CTC	0.0161	0.0181	0.0417	0.0322



(a)



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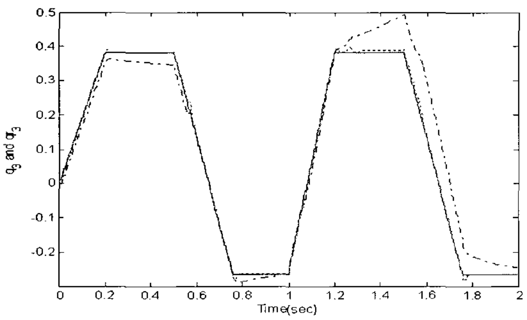

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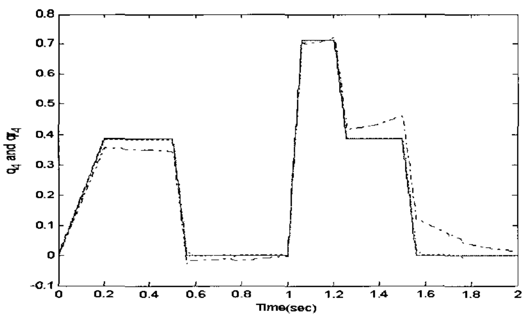


(d)

Fig. 4. Comparison of tracking results for five-link biped robot (a) q_1 (b) q_2 (c) q_3 (d) q_4 (solid line: reference value, dotted line: SRWNNABC, dash-dotted line: CTC).

diagonal matrices, respectively.

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 by online parameter tuning methodology. Fig. 4 compares the actual joint angles of the SRWNNABC and the CTC system. The tracking error cost functions are compared in Figs. 5 and 6. These figures reveal that the proposed control system gives the excellent performance compared to the CTC system even under the influence of the time-varying uncertainties and external disturbances. The average tracking errors e_1, e_2, e_3, and e_4 of q_1, q_2, q_3, and q_4 are compared in Table 2.

In Table 2, note that the average tracking errors of the CTC is more than ten times of the corresponding errors of the SRWNNABC. Fig. 7 displays the driving torques of the biped robot system with the SRWNNABC. The reference locomotion mode and locomotion mode controlled by the SRWNNABC of the biped robot on the horizontal surface

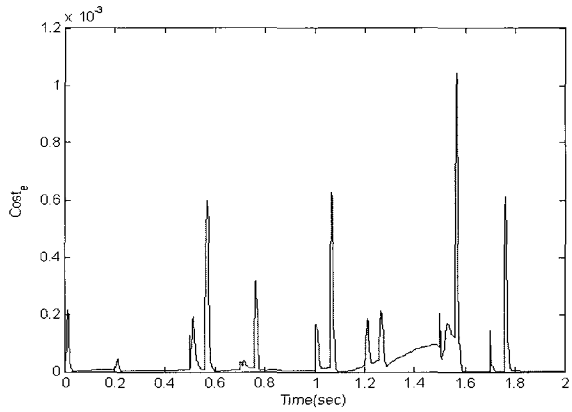


Fig. 5. Error cost function of SRWNNABC.

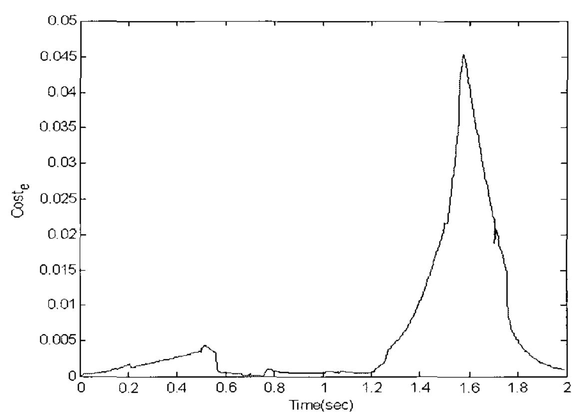


Fig. 6. Error cost function of CTC.

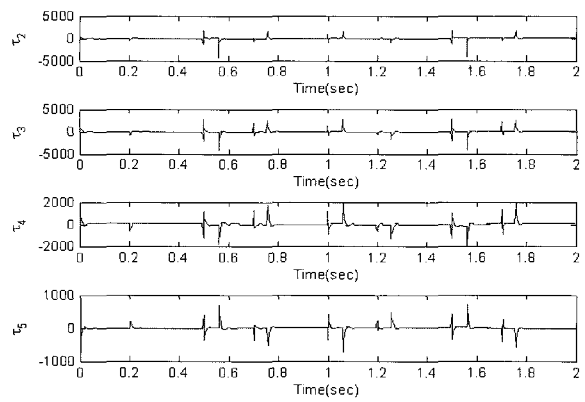


Fig. 7. Driving torques of the five-link biped robot with the SRWNNABC.

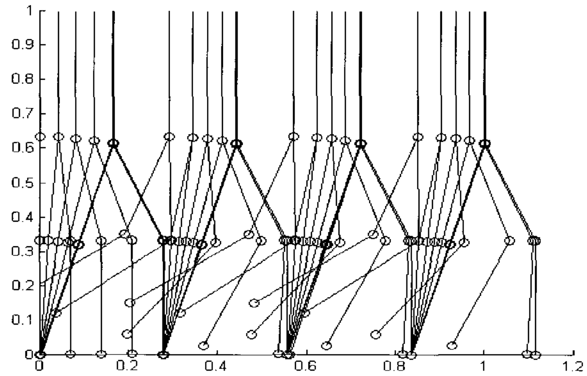


Fig. 8. Reference locomotion mode of the five-link biped robot.

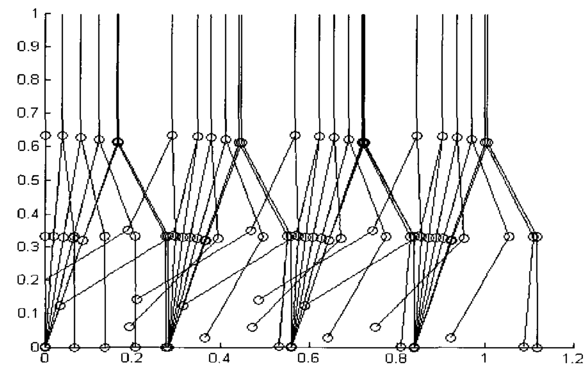


Fig. 9. Controlled locomotion mode of the five-link biped robot with the SRWNNABC.

are shown in Figs. 8 and 9. Note that two locomotion modes have almost similar forms. As a result, the suggested method can overcome unknown model uncertainties resulting from the biped robot dynamics and external disturbances.

V. Conclusion

In this paper, we have proposed the SRWNNABC system for stable walking of the biped robots with unknown model uncertainties. The SRWNNs composed of simple structures have been employed as the uncertainty observer and the error compensator has been used to compensate the observed error induced by the SRWNN uncertainty observer. The adaptation laws for weights of the SRWNN and the error compensator have been induced from the Lyapunov stability theorem, which have been used for guaranteeing the asymptotic stability of the SRWNNABC system. Finally, the five-link biped robot has been simulated for verifying the robustness and disturbance rejection ability of the proposed control system.

References

[1] S. Tzafestas, M. Raibert, and C. Tzafestas, "Robust sliding-mode control applied to a 5-link biped robot," *Jour. of Intelligent and Robotic Systems*, vol. 15, pp. 67-133, 1996.

[2] H. K. Lum, M. Zribi, and Y. C. Soh, "Planning and control of a biped robot," *Int. Jour. of Engineering Science,* vol 37, no. 10, pp. 1319-1349, 1999.

[3] L. C. Kwek, E. K. Wong, C. K. Loo, and M. V. C. Rao, "Application of active force control and iterative learning in a 5-link biped robot," *Jour. of Intelligent and Robotic systems*, vol. 37, pp. 143-162, 2003.

[4] M. Krstic, I. Kanellakopoulos, and P. Kokotovic, *Nonlinear and adaptive control design*, NJ : Wiley Interscience, 1995.

[5] H. K. Khalil, *Nonlinear Systems,* Upper Saddle River, NJ: Prentice-Hall, 1996.

[6] S. J. Yoo, J. B. Park, and Y. H. Choi, "Stable predictive control of chaotic systems using self-recurrent wavelet neural network," *Int. Jour. of Control, Automation, and Systems*, vol. 3, no. 1, pp. 43-55, 2005.

[7] S. J. Yoo, J. B. Park, and Y. H. Choi, "Direct adaptive control using self recurrent wavelet neural network via adaptive learning rates for stable path tracking of mobile robots," *Proc. of American Control Conference*, pp. 288-293, 2005.

[8] Q. Zhang and A. Benveniste, "Wavelet networks," *IEEE Trans. Neural Networks*, vol. 3, no. 6, pp. 889-898, 1992.

[9] F. J. Lin, T. S. Lee, and C. H. Lin, "Robust H_∞ controller design with recurrent neural network for linear synchronous motor drive," *IEEE Trans. Industrial Electronics*, vol. 50, no. 3, pp. 456-470, 2003.

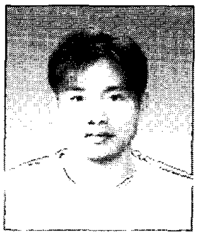
[10] E. Kim, "Output feedback tracking control of robot manipulators with model uncertainty via adaptive fuzzy logic," *IEEE Trans. Fuzzy Systems,* vol. 12, no 3, pp. 368-378, 2004.

[11] X. Mu, and Q. Wu, "Development of a complete dynamic model of a planar five-link biped and sliding mode control of its locomotion during the double

support phase," *Int. Jour. of Control,* vol. 77, no. 8, pp. 789-799, 2004.

[12] F. L. Lewis, C. T. Abdallah, and D. M. Dawson, *Control of Robot Manipulators*. New York: Macmillan, 1993.

[13] C. Y. Lee, and J. J. Lee, "Multiple neuro-adaptive control of robot manipulators using visual cues," *IEEE Trans. Industrial Electronics,* vol. 52, no. 1, pp. 320-326, 2005.



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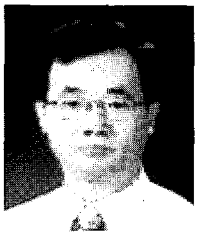

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