Robust Control of Planar Biped Robots in Single Support Phase Using Intelligent Adaptive Backstepping Technique

Sung Jin Yoo, Jin Bae Park*, and Yoon Ho Choi

Abstract: This paper presents a robust control method via the intelligent adaptive backstepping design technique for stable walking of nine-link biped robots with unknown model uncertainties and external disturbances. In our control structure, the self recurrent wavelet neural network (SRWNN) which has the information storage ability is used to observe the uncertainties of the biped robots. The adaptation laws for all weights of the SRWNN are induced from the Lyapunov stability theorem, which are used for on-line controlling biped robots. Also, we prove that all signals in the closed-loop adaptive system are uniformly ultimately bounded. Through computer simulations of a nine-link biped robot with model uncertainties and external disturbances, we illustrate the effectiveness of the proposed control system.

Keywords: Backstepping design, biped robot, recurrent wavelet neural network, robust control.

1. INTRODUCTION

The biped robots have been received increased attention due to several properties such as its human-like mobility and the high-order dynamic equation. These properties enable the biped robots to perform the dangerous works instead of human beings. Thus, the stable walking control of the biped robots is a fundamentally hot issue and has been studied by many researchers [1-9]. However, because of the inherent instability caused by two legged locomotion, it is difficult to control the biped robots. Besides, unlike the robot manipulator, the biped robot has an uncontrollable degree of freedom playing a dominant role for the stability of their locomotion in the biped robot dynamics. In recent year, various control techniques such as computed torque control [1,2], sliding model control [2,3], active force control [4] are applied to control the biped robot. Especially, [2] and [5] have contributed for the dynamic modeling and robust control of the five-link biped robot and the nine-link biped robot, respectively. 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, it is difficult to predict or to know in advance the parameter variations of the biped robot system and the external disturbances changed according to the environment. In the case of [4], the active force control known as "disturbance rejector" is applied to control the five-link biped robot, but the model uncertainties of the robot system are not considered. That is, the external disturbance is only treated.

Generally, the complete three-dimensional walking motion of the biped robot can be explained by a single support phase, a double support phase, double impact, switching transformation, and by motion in the sagittal plane as well as in the lateral plane [6-8]. 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 [1,9]. Accordingly, in this paper, to examine the feasibility of the proposed control scheme, we consider the motion of the biped robot in sagittal plane during the single support phase.

On the other hand, neural networks (NNs) have been applied as an attractive tool to approximate the complex nonlinear systems due to their excellent learning capabilities and parallel processing structures. Recently, wavelet neural networks (WNNs), which absorbs the advantages of high resolution of wavelets and learning of NNs, have been proposed to guarantee the fast convergence and have been used for the identification and control of nonlinear systems [10-12]. However, the WNN does not require prior knowledge about the plant to be controlled due to its feedforward structure. Therefore, without the aid of tapped delays,

Manuscript received March 20, 2006; revised December 2, 2006; accepted March 8, 2007. Recommended by Editorial Board member Sooyong Lee under the direction of Editor Jae-Bok Song. This work was supported by the Brain Korea 21 Project in 2006.

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the WNN is unable to represent a dynamic mapping. Accordingly, we proposed the self recurrent wavelet neural network (SRWNN), which combines the properties of attractor dynamics of recurrent neural network (RNN) and the fast convergence of WNN, and applied successfully it to the estimation and control of nonlinear systems [13,14]. In [8,9,15], NN-based control systems have been developed for biped robot systems.

The adaptive backstepping control is a systematic and recursive design methodology for the feedback control of nonlinear systems with parametric uncertainties. Unlike the feedback linearization method with the problems such as the precise model requirement and the cancellation of useful nonlinear terms, the backstepping approach offers a choice of design tools for accommodation of uncertainties and nonlinearities, and can avoid wasteful cancellations [16]. The key idea of the 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 [16]. Therefore, the finally designed actual control law can guarantee the stability of total control system. In spite of these advantages of the backstepping design, the adaptive backstepping control method has two major problems: "linearity in the unknown system parame-ers" and "determination of the regression matrix" [17]. To eliminate these defects, Kwan and Lewis [17] proposed the NN based robust backstepping control method for nonlinear robotic systems with arbitrary uncertainties.

In this paper, the intelligent adaptive backstepping control (IABC) method using the powerful approximation ability of the SRWNN is proposed for stable walking of biped robots. The internal uncertainties and external disturbances of the biped robot system are first integrated in the robot dynamics, then the SRWNN is employed as the uncertainty observer to estimate the integrated total uncertainty term. The adaptation laws for weights of the uncertainty observer are induced from the Lyapunov stability theorem, which are used to guarantee the uniform ultimate boundedness of all signals in the closed-loop system. Finally, the simulation results for the nine-link biped robot are provided to demonstrate the effectiveness of the proposed control scheme.

This paper is organized as follows. In Section 2, we introduce the model of biped robot systems with uncertainties and the basics of the SRWNN, and present the robust control problem for the biped robot system. In Section 3, the IABC system for solving the robust control problem of the biped robot system is proposed. In addition, the stability, robustness, and performance of the proposed control system are analyzed based on Lyapunov stability theorem. Simulation results are discussed to confirm the effectiveness and applicability of the proposed method in Section 4. Finally, Section 5 gives some conclusions.

2. PRELIMINARIES

2.1. Model of planar biped robots with uncertainties

The dynamics of the biped robot with model uncertainties in the single support phase can be expressed in the following Lagrange form [18]:

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

where

$$\Pi(\mathbf{q},\dot{\mathbf{q}},\tau) = -\mathbf{M}(\mathbf{q})\bar{\mathbf{M}}^{-1}(\mathbf{q})\{\tau - \tau_d - \bar{\mathbf{C}}(\mathbf{q},\dot{\mathbf{q}}) - \bar{\mathbf{G}}(\mathbf{q}) - \bar{\mathbf{F}}(\dot{\mathbf{q}})\} + \{\tau - \mathbf{C}(\mathbf{q},\dot{\mathbf{q}}) - \mathbf{G}(\mathbf{q}) - \mathbf{F}(\dot{\mathbf{q}})\}.$$

denotes the uncertainty of the robot system, and $\mathbf{q}$, $\dot{\mathbf{q}}$, $\ddot{\mathbf{q}} \in R^n$ are the joint position, velocity, and acceleration, respectively. $\mathbf{M}(\mathbf{q}) \in R^{n\times n}$ is the inertia matrix, $\mathbf{C}(\mathbf{q},\dot{\mathbf{q}}) \in R^n$ denotes the Coriolis and centrifugal torques, $\mathbf{G}(\mathbf{q}) \in R^n$ is the gravity vector, $\mathbf{F}(\dot{\mathbf{q}}) \in R^n$ represents the friction term, and the control input torque is $\tau \in R^n$. Also, $\bar{\mathbf{M}}(\mathbf{q})$, $\bar{\mathbf{C}}(\mathbf{q},\dot{\mathbf{q}})$, $\bar{\mathbf{G}}(\mathbf{q})$, and $\bar{\mathbf{F}}(\dot{\mathbf{q}})$ are the actual values with uncertainties in the nominal values $\mathbf{M}(\mathbf{q})$, $\mathbf{C}(\mathbf{q},\dot{\mathbf{q}})$, $\mathbf{G}(\mathbf{q})$, and $\mathbf{F}(\dot{\mathbf{q}})$, respectively. $\tau_d \in R^n$ is the external disturbance.

Assumption 1: Assume that the nominal values $\mathbf{M}(\mathbf{q})$, $\mathbf{C}(\mathbf{q},\dot{\mathbf{q}})$, $\mathbf{G}(\mathbf{q})$, and $\mathbf{F}(\dot{\mathbf{q}})$ are only known values for a given biped robot. That is, suppose that the actual values $\bar{\mathbf{M}}(\mathbf{q})$, $\bar{\mathbf{C}}(\mathbf{q},\dot{\mathbf{q}})$, $\bar{\mathbf{G}}(\mathbf{q})$, and $\bar{\mathbf{F}}(\dot{\mathbf{q}})$ and the external disturbance τ_d are the unknown values.

Assumption 2: The system states $\mathbf{q}$ and $\dot{\mathbf{q}}$ are all available for feedback.

From Assumption 1, the uncertainty term $\Pi(\mathbf{q}, \dot{\mathbf{q}},\tau)$ cannot be computed. Accordingly, in this paper, we consider the control problem of the nine-link biped robot with the uncertainty term $\Pi(\mathbf{q},\dot{\mathbf{q}},\tau)$.

2.2. SRWNN structure

The SRWNN has N_i inputs, one output, and $N_i \times N_w$ mother wavelets and consists of four layers: an input layer, a mother wavelet layer, a product layer, and an output layer [14]. Each node of a mother wavelet layer has a mother wavelet and a self-feedback loop. The SRWNN output y is defined as follows:

$$y(N)=\sum_{j=1}^{N_w} w_j\Phi_j(N)+\sum_{k=1}^{N_i} a_k x_k(N), \tag{2}$$

where N denotes the number of iterations, x_k represents the k-th input of the SRWNN, w_j is the j-th connection weight between product nodes and output nodes, a_k is the k-th connection weight between the input nodes and the output node, and the term $\Phi_j(N)$ is defined as

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

where the subscript jk indicates the k-th input term of the j-th wavelet, $\phi(x)$ denotes the mother wavelet function defined as $\phi(x)=-x\exp(-\frac{1}{2}x^2)$ which has the universal approximation property [12], m_{jk} and d_{jk} are the translation factor and the dilation factor of the wavelets, respectively. In addition, the inputs u_{jk} of the wavelet nodes can be denoted by

$$u_{jk}(N)=x_k(N)+\phi_{jk}(N-1)\cdot\theta_{jk}, \tag{3}$$

where θ_{jk} denotes the weight of the self-feedback loop. The input of mother wavelet layer contains the memory term $\phi_{jk}(N-1)$, which can store the past information of the network. 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 analysis. For this end, the weighting vector $\mathbf{W}\in R^{3N_wN_i+N_w+N_i}$ is defined as

$$\begin{aligned}\mathbf{W}=[&a_1 \ a_2 \ \cdots \ a_{N_i} \ m_{11} \ m_{12} \ \cdots \ m_{1N_i} \ m_{21} \ \cdots \\ &m_{2N_i} \ \cdots \ m_{N_wN_i} \ d_{11} \ d_{12} \ \cdots \ d_{1N_i} \ d_{21} \ \cdots \\ &d_{2N_i} \ \cdots \ d_{N_wN_i} \ \theta_{11} \ \theta_{12} \ \cdots \ \theta_{1N_i} \ \theta_{21} \ \cdots \\ &\theta_{2N_i} \ \cdots \ \theta_{N_wN_i} \ w_1 \ \cdots \ w_{N_w}]^T.\end{aligned} \tag{4}$$

3. INTELLIGENT ADAPTIVE BACKSTEPING CONTROL SYSTEM

In this section, we design the robust control system via the adaptive backstepping technique using the SRWNN uncertainty observer. The dynamics (1) is rewritten by using state variables $\mathbf{X}_1=\mathbf{q}$ and $\mathbf{X}_2=\dot{\mathbf{q}}$ as follows:

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

The control objective is to produce an adaptive control law for the state vector $\mathbf{X}_1$ to track the reference trajectory vector $\mathbf{q_d}$. Here, it is assumed that $\mathbf{q_d}$, $\dot{\mathbf{q}}_\mathbf{d}$, and $\ddot{\mathbf{q}}_\mathbf{d}$, which denote the desired position, velocity, and acceleration, respectively, are the bounded functions of the time. We now design the intelligent adaptive controller via the backstepping design technique [16] shown in Fig. 1 step by step.

Step 1: Design the virtual controller $\mathbf{X}_2$.

For the tracking control of the state $\mathbf{X}_1(t)$, define the tracking error as

$$\mathbf{Z}_1(t)=\mathbf{X}_1(t)-\mathbf{q_d}(t), \tag{6}$$

and its derivative is

$$\begin{aligned}\dot{\mathbf{Z}}_1(t)&=\dot{\mathbf{X}}_1(t)-\dot{\mathbf{q}}_\mathbf{d}(t)\\ &=\mathbf{v}(t)-\dot{\mathbf{q}}_\mathbf{d}(t),\end{aligned} \tag{7}$$

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

$$\mathbf{s}(t)=-\mathbf{K}_1\mathbf{Z}_1(t)+\dot{\mathbf{q}}_\mathbf{d}(t), \tag{8}$$

where $\mathbf{K}_1$ is a positive definite diagonal matrix. The first Lyapunov function is chosen as

$$V_1(t)=\frac{1}{2}\mathbf{Z}_1^{\mathrm{T}}(t)\mathbf{Z}_1(t). \tag{9}$$

Then, its derivative is

$$\begin{aligned}\dot{V}_1(t)&=\mathbf{Z}_1^{\mathrm{T}}(t)\dot{\mathbf{Z}}_1(t)\\ &=\mathbf{Z}_1^{\mathrm{T}}(t)(\dot{\mathbf{X}}_1(t)-\dot{\mathbf{q}}_\mathbf{d}(t))\\ &=\mathbf{Z}_1^{\mathrm{T}}(t)(\mathbf{v}(t)-\mathbf{s}(t)-\mathbf{K}_1\mathbf{Z}_1(t)).\end{aligned} \tag{10}$$

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

Step 2: Design the actual controller τ.

To design the actual controller τ, we define $\mathbf{Z}_2(t)$ as $\mathbf{Z}_2(t)=\mathbf{v}(t)-\mathbf{s}(t)$. And then, the derivative of $\mathbf{Z}_2(t)$ is expressed as

$$\begin{aligned}\dot{\mathbf{Z}}_2(t)&=\dot{\mathbf{v}}(t)-\dot{\mathbf{s}}(t)\\ &=\dot{\mathbf{X}}_2(t)+\mathbf{K}_1\dot{\mathbf{Z}}_1(t)-\ddot{\mathbf{q}}_\mathbf{d}(t)\\ &=\mathbf{M}^{-1}(\mathbf{X}_1)\{\tau-\mathbf{C}(\mathbf{X}_1,\mathbf{X}_2)-\mathbf{G}(\mathbf{X}_1)-\mathbf{F}(\mathbf{X}_2)\}\\ &\quad+\Gamma(\mathbf{X}_1,\mathbf{X}_2,\tau)+\mathbf{K}_1\dot{\mathbf{Z}}_1(t)-\ddot{\mathbf{q}}_\mathbf{d}(t),\end{aligned} \tag{11}$$

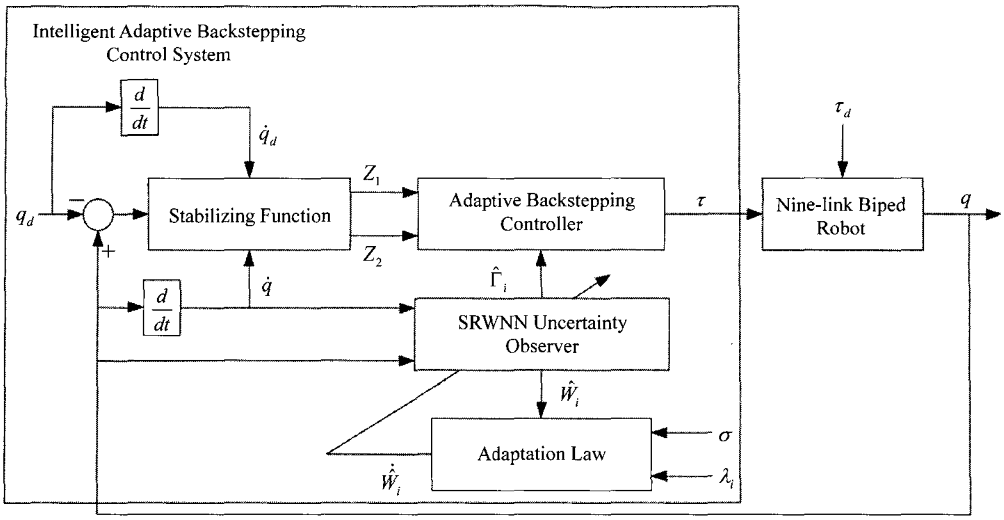


Fig. 1. Block diagram of the proposed IABC system.

where $\Gamma(\mathbf{X}_1,\mathbf{X}_2,\tau)=-\mathbf{M}^{-1}(\mathbf{X}_1)\Pi(\mathbf{X}_1,\mathbf{X}_2,\tau)$ is the uncertainty term, τ is a function of $\mathbf{X}_1$, $\mathbf{X}_2$, and $\mathbf{Q}_\mathbf{d}=[\mathbf{q}_\mathbf{d}\ \ \dot{\mathbf{q}}_\mathbf{d}\ \ \ddot{\mathbf{q}}_\mathbf{d}]^\mathrm{T}$. Accordingly, the uncertainty term can be represented by $\Gamma(\mathbf{X}_1,\mathbf{X}_2,\tau)=\Gamma(\mathbf{X}_1,\mathbf{X}_2,\mathbf{Q}_\mathbf{d})$. To design the backstepping control system, the Lyapunov function is defined as

$$V_2(\mathbf{Z}_1(t),\mathbf{Z}_2(t))=V_1(t)+\frac{1}{2}\mathbf{Z}_2^\mathrm{T}(t)\mathbf{Z}_2(t). \tag{12}$$

And its derivative can be derived as follows:

$$\begin{aligned}\dot{V}_2&=\dot{V}_1+\mathbf{Z}_2^\mathrm{T}(t)\dot{\mathbf{Z}}_2(t)\\&=\mathbf{Z}_1^\mathrm{T}(t)(\mathbf{Z}_2(t)-\mathbf{K}_1\mathbf{Z}_1(t))+\mathbf{Z}_2^\mathrm{T}(t)\\&\quad\times[\mathbf{M}^{-1}(\mathbf{X}_1)\{\tau-\mathbf{C}(\mathbf{X}_1,\mathbf{X}_2)-\mathbf{G}(\mathbf{X}_1)\\&\quad-\mathbf{F}(\mathbf{X}_2)\}+\Gamma(\mathbf{X}_1,\mathbf{X}_2,\mathbf{Q}_\mathbf{d})+\mathbf{K}_1\dot{\mathbf{Z}}_1(t)-\ddot{\mathbf{q}}_\mathbf{d}(t)].\end{aligned} \tag{13}$$

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

$$\begin{aligned}\tau&=\mathbf{C}(\mathbf{X}_1,\mathbf{X}_2)+\mathbf{G}(\mathbf{X}_1)+\mathbf{F}(\mathbf{X}_2)\\&\quad+\mathbf{M}(\mathbf{X}_1)[-\Gamma(\mathbf{X}_1,\mathbf{X}_2,\mathbf{Q}_\mathbf{d})-\mathbf{K}_1\dot{\mathbf{Z}}_1(t)\\&\quad+\ddot{\mathbf{q}}_\mathbf{d}-\mathbf{K}_2\mathbf{Z}_2(t)-\mathbf{Z}_1(t)],\end{aligned} \tag{14}$$

where $\mathbf{K}_2$ is a positive definite diagonal matrix, from (13), the backstepping control system is the asymptotic stable. However, since the uncertainty term $\Gamma(\mathbf{X}_1,\mathbf{X}_2,\mathbf{Q}_\mathbf{d})$ is the unknown value, τ cannot be evaluated exactly.

Step 3: Design the intelligent adaptive backstepping controller τ.

To proceed with the controller development, the following assumption is required.

Assumption 3: Let the input $\mathbf{X}$ of the SRWNN belong to a compact set K_X, and the SRWNN is used to approximate the nonlinear function $\Gamma(\mathbf{X})$. The optimal parameter vector $\mathbf{W}^*$ of the SRWNN $\hat{\Gamma}(\cdot)$ is given as

$$\mathbf{W}^*=\arg\min_{\hat{\mathbf{W}}\in K_W}\left[\sup_{\mathbf{X}\in K_X}\left\|\Gamma(\mathbf{X})-\hat{\Gamma}(\mathbf{X}\,|\,\hat{\mathbf{W}})\right\|\right], \tag{15}$$

where K_W is a compact set of the parameter vector, $K_W=\{\hat{\mathbf{W}}\,|\,\|\hat{\mathbf{W}}\|\le k_w\}$ denotes a ball of radius k_w, and it is assumed that the optimal parameter vector $\mathbf{W}^*$ is also restricted to K_W.

According to the powerful approximation ability [13], we employ the SRWNN uncertainty observer to estimate the nonlinear uncertainty term $\Gamma(\mathbf{X}_1,\mathbf{X}_2,\mathbf{Q}_\mathbf{d})$ to a sufficient degree of accuracy. The inputs of the SRWNN are the states $\mathbf{X}_1$ and $\mathbf{X}_2$, and its output is $\hat{\Gamma}$. Thus the uncertainty term $\Gamma(\mathbf{X}_1,\mathbf{X}_2,\mathbf{Q}_\mathbf{d})$ can be described by the optimal SRWNN plus a reconstruction error vector ε as follows:

$$\begin{aligned}\Gamma(\mathbf{X})&=\Gamma^*(\mathbf{X}\,|\,\mathbf{W}^*)+\varepsilon\\&=\hat{\Gamma}(\mathbf{X}\,|\,\hat{\mathbf{W}})+[\Gamma^*(\mathbf{X}\,|\,\mathbf{W}^*)-\hat{\Gamma}(\mathbf{X}\,|\,\hat{\mathbf{W}})]+\varepsilon,\end{aligned} \tag{16}$$

where $\mathbf{X}=(\mathbf{X}_1,\mathbf{X}_2)$, $\hat{\mathbf{W}}=diag[\hat{W}_i]$; $\hat{W}_i\in R^{3N_wN_i+N_w+N_i}$ $(i=1,2,\ldots,n)$ is the estimated vector of weighting vector $\mathbf{W}$ of the SRWNN defined in Section 2.2. Here, $diag[\cdot]$ denotes a diagonal matrix and $\mathbf{W}^*$ is the optimal weighting matrix that achieves the minimum reconstruction error.

Assumption 4: Assume that the optimal weight matrix is bounded as follows:

$$\|\mathbf{W}^*\|_F\le W_M, \tag{17}$$

where $\|\cdot\|_F$ denotes the Frobenius norm.

Note that the bounded value W_M is not required to implement the controller proposed in this paper. This value is only used for the stability analysis of the proposed control system.

Taking the Taylor series expansion of $\hat{\Gamma}(\mathbf{X}\,|\,\hat{\mathbf{W}})$ around $\hat{\mathbf{W}}$ for the training of all weights of the SRWNN uncertainty observer, we can obtain [19]

$$\Gamma^*(\mathbf{X}\,|\,\mathbf{W}^*)-\hat{\Gamma}(\mathbf{X}\,|\,\hat{\mathbf{W}})=\tilde{\mathbf{W}}^{\mathrm{T}}\Theta_{\mathrm{W}}+\mathbf{H}(\mathbf{W}^*,\hat{\mathbf{W}}),\quad(18)$$

where $\mathbf{H}(\mathbf{W}^*,\hat{\mathbf{W}})$ is a high-order term,

$$\tilde{\mathbf{W}}(t)=\mathbf{W}^*-\hat{\mathbf{W}}(t),\quad(19)$$

and

$$\Theta_{\mathrm{W}}=\left[\frac{\partial\hat{\Gamma}_1(X\,|\,\hat{W}_1)}{\partial\hat{W}_1}\ \ \frac{\partial\hat{\Gamma}_2(X\,|\,\hat{W}_2)}{\partial\hat{W}_2}\ \ \cdots\ \ \frac{\partial\hat{\Gamma}_n(X\,|\,\hat{W}_n)}{\partial\hat{W}_n}\right]^T.$$

Substituting (18) into (16), (16) can be represented by

$$\begin{aligned}\Gamma(\mathbf{X})&=\Gamma^*(\mathbf{X}\,|\,\mathbf{W}^*)+\varepsilon\\&=\hat{\Gamma}(\mathbf{X}\,|\,\hat{\mathbf{W}})+\tilde{\mathbf{W}}^{\mathrm{T}}\Theta_{\mathrm{W}}+\alpha,\end{aligned}\quad(20)$$

$$\|\alpha\|\le\rho,\quad(21)$$

where $\alpha=\mathbf{H}(\mathbf{W}^*,\hat{\mathbf{W}})+\varepsilon$ and ρ is a positive constant. We propose the intelligent adaptive backstepping control law as follows:

$$\begin{aligned}\tau&=\mathbf{C}(\mathbf{X}_1,\mathbf{X}_2)+\mathbf{G}(\mathbf{X}_1)+\mathbf{F}(\mathbf{X}_2)\\&\quad+\mathbf{M}(\mathbf{X}_1)[-\hat{\Gamma}(\mathbf{X}\,|\,\hat{\mathbf{W}})-\mathbf{K}_1\dot{\mathbf{Z}}_1\\&\quad+\ddot{\mathbf{q}}_{\mathbf{d}}-\mathbf{K}_2\mathbf{Z}_2-\mathbf{Z}_1].\end{aligned}\quad(22)$$

Theorem 1: Suppose that the nine-link biped robot (1) with model uncertainties and external disturbances in the single support phase is controlled by the proposed controller (22). And if the proposed control system satisfies Assumptions 1-4 and the adaptation law for all weights of the SRWNN system is chosen as follows:

$$\dot{\hat{W}}_i=\lambda_i\Theta_{W,i}Z_{2,i}-\sigma\lambda_i\hat{W}_i,\quad(23)$$

where $i=1,\ldots,n$, $\lambda_i>0$ which is a diagonal element of λ is the tuning gain, σ is the positive constant, and $\Theta_{W,i}$ and $Z_{2,i}$ are the i-th elements of Θ_{W} and $\mathbf{Z}_2$, respectively, then

(i) there exist $\mathbf{K}_1$, $\mathbf{K}_2$, λ_i, and σ such that the errors of states and adjustable weights of the closed-loop system are uniformly ultimately bounded. Also, these errors may be kept arbitrarily small by adjusting the design parameters in the control law and the adaptation law.

(ii) for the error vector $\mathbf{E}=[\mathbf{Z}_1^{\mathrm{T}}\ \mathbf{Z}_2^{\mathrm{T}}\ \|\tilde{\mathbf{W}}\|_F]^T$, the error vector $\mathbf{E}$ satisfies the following inequality:

$$\|\mathbf{E}(t)\|^2\le\frac{\gamma_M}{\gamma_m}\|\mathbf{E}(t_0)\|^2e^{-2\zeta(t-t_0)}+\frac{P\gamma_M}{\zeta}[1-e^{-2\zeta(t-t_0)}],\quad(24)$$

where $\gamma_M=\max[1,\lambda_M]$, $\gamma_m=\max[1,\lambda_m]$. Here, λ_M and λ_m are the maximum and minimum eigenvalue of λ, respectively. Besides, L_∞ *norm* of the error vector $\mathbf{E}$ can be obtained as

$$\|\mathbf{E}(t)\|_\infty=\max\left[\sqrt{\frac{\gamma_M}{\gamma_m}}\|\mathbf{E}(t_0)\|,\sqrt{\frac{P\gamma_M}{\zeta}}\right].\quad(25)$$

Proof:

(i) A Lyapunov candidate is chosen as

$$V_3=V_2+\frac{1}{2}tr(\tilde{\mathbf{W}}^{\mathrm{T}}\lambda^{-1}\tilde{\mathbf{W}}),\quad(26)$$

where $tr(\cdot)$ denotes the trace of a matrix. Differentiating the Lyapunov function (26) and using (20) and (22), we can obtain

$$\begin{aligned}\dot{V}_3&=\dot{V}_2-tr(\tilde{\mathbf{W}}^{\mathrm{T}}\lambda^{-1}\dot{\hat{\mathbf{W}}})\\&\le-\mathbf{Z}_1^{\mathrm{T}}\mathbf{K}_1\mathbf{Z}_1-\mathbf{Z}_2^{\mathrm{T}}\mathbf{K}_2\mathbf{Z}_2+\|\mathbf{Z}_2\|\|\alpha\|\\&\quad-tr\{\tilde{\mathbf{W}}^{\mathrm{T}}(\lambda^{-1}\dot{\hat{\mathbf{W}}}-\Theta_{\mathrm{W}}\mathbf{Z}_2^{\mathrm{T}})\}.\end{aligned}\quad(27)$$

Then, using (21) and if the adaptation law (23) are applied to the above equation, we can obtain

$$\dot{V}_3\le-\mathbf{Z}_1^{\mathrm{T}}\mathbf{K}_1\mathbf{Z}_1-\mathbf{Z}_2^{\mathrm{T}}\mathbf{K}_2\mathbf{Z}_2+\|\mathbf{Z}_2\|\rho+\sigma tr(\tilde{\mathbf{W}}^{\mathrm{T}}\hat{\mathbf{W}}).\quad(28)$$

Using (19), Assumption 4, and the fact $\|\mathbf{Z}_2\|\rho\le\|\mathbf{Z}_2\|^2+\frac{1}{4}\rho^2$,

$$\begin{aligned}\dot{V}_3&\le-\mathbf{Z}_1^{\mathrm{T}}\mathbf{K}_1\mathbf{Z}_1-\mathbf{Z}_2^{\mathrm{T}}\mathbf{K}_2\mathbf{Z}_2\\&\quad+\|\mathbf{Z}_2\|^2+\frac{1}{4}\rho^2+\sigma(\|\tilde{\mathbf{W}}\|_FW_M-\|\tilde{\mathbf{W}}\|_F^2).\end{aligned}$$

Here, choosing $\mathbf{K}_2=\mathbf{I}+\mathbf{K}_2^*$; $\mathbf{I}$ and $\mathbf{K}_2^*$ denote the $n\times n$ identity matrix and the positive definite diagonal matrix, respectively, and applying $\sigma(\|\tilde{\mathbf{W}}\|_FW_M-\|\tilde{\mathbf{W}}\|_F^2)\le-\frac{1}{2}\sigma\|\tilde{\mathbf{W}}\|_F^2+\frac{1}{2}\sigma W_M^2$,

$$\begin{aligned}\dot{V}_3&\le-\mathbf{Z}_1^{\mathrm{T}}\mathbf{K}_1\mathbf{Z}_1-\mathbf{Z}_2^{\mathrm{T}}\mathbf{K}_2\mathbf{Z}_2+\|\mathbf{Z}_2\|^2+\frac{1}{4}\rho^2\\&\quad-\frac{1}{2}\sigma\|\tilde{\mathbf{W}}\|_F^2+\frac{1}{2}\sigma W_M^2\\&\le-\mathbf{Z}_1^{\mathrm{T}}\mathbf{K}_1\mathbf{Z}_1-\mathbf{Z}_2^{\mathrm{T}}\mathbf{K}_2^*\mathbf{Z}_2-\frac{1}{2}\sigma\|\tilde{\mathbf{W}}\|_F^2+P,\end{aligned}\quad(29)$$

where $P=\frac{1}{2}\sigma W_M^2+\frac{1}{4}\rho^2$.

Then, let us choose the constant ζ satisfying the following condition:

$$0<\zeta<\min\left[K_{1,m}, K_{2,m}^{*}, \frac{\sigma\lambda_m}{2}\right], \tag{30}$$

Where $K_{1,m}$, $K_{2,m}^{*}$, and λ_m are the minimum eigenvalues of $\mathbf{K}_1$, $\mathbf{K}_2^{*}$, and λ, respectively. Hence, (29) can be represented by

$$\dot{V}_3\le -2\zeta V_3+P. \tag{31}$$

This relation implies that $\dot{V}_3<0$ when $V_3>P/2\zeta$. Accordingly, $\mathbf{Z}_1$, $\mathbf{Z}_2$, and $\tilde{\mathbf{W}}$ are uniformly ultimately bounded in the following compact set Ω:

$$\Omega=\left\{\mathbf{Z}_1,\mathbf{Z}_2,\tilde{\mathbf{W}}\middle|\mathbf{Z}_1^{\mathrm{T}}\mathbf{Z}_1+\mathbf{Z}_2^{\mathrm{T}}\mathbf{Z}_2+\frac{1}{\lambda_M}\|\tilde{\mathbf{W}}\|_F^2\le\frac{P}{\zeta}\right\}, \tag{32}$$

where λ_M is a maximum eigenvalue of λ. Besides, the compact set Ω can be kept arbitrarily small by adjusting $\mathbf{K}_1$, $\mathbf{K}_2^{*}$, and λ. That is, the tracking error $\mathbf{Z}_1$ can be made arbitrarily small.

(ii) Define $\Psi(t)=\dot{V}_3+2\zeta V_3-P$. Solving the first-order differential equation, the solution of V_3 can be computed by

$$\begin{aligned} V_3(t)&=e^{-2\zeta(t-t_0)}V_3(t_0)+P\int_{t_0}^{t}e^{-2\zeta(t-r)}dr \\ &\quad+\int_{t_0}^{t}e^{-2\zeta(t-r)}\Psi(t)dr, \end{aligned} \tag{33}$$

where $0\le t_0\le\forall t$. From (31), we can know that $\Psi(t)\le 0$. Therefore,

$$V_3(t)\le e^{-2\zeta(t-t_0)}V_3(t_0)+\frac{P}{2\zeta}[1-e^{-2\zeta(t-t_0)}]. \tag{34}$$

Using the fact $(1/2\gamma_M)\|\mathbf{E}\|^2\le V_3\le(1/2\gamma_m)\|\mathbf{E}\|^2$, the inequality (34) can be rewritten as follows:

$$\|\mathbf{E}(t)\|^2\le\frac{\gamma_M}{\gamma_m}\|\mathbf{E}(t_0)\|^2e^{-2\zeta(t-t_0)}+\frac{P\gamma_M}{\zeta}[1-e^{-2\zeta(t-t_0)}]. \tag{35}$$

In (35), we can find that $\|\mathbf{E}(t)\|^2$ increases or decreases monotonically between the values of $\frac{\gamma_M}{\gamma_m}\|\mathbf{E}(t_0)\|^2$ and $\frac{P\gamma_M}{\zeta}$. So, L_∞ *norm* of the error vector $\mathbf{E}$ is obtained as (25). Besides, note that from (35), $\|\mathbf{E}(t)\|_\infty\to\sqrt{P\gamma_M/\zeta}$ as $t\to\infty$. This completes the proof of the theorem.

Remark 1: 1) In the adaptation law (23) for weighting vectors of the SRWNN uncertainty observer, σ-modification technique [20] is used to prevent parameter drift. Also, we can use a projection operator method [21], and e-modification method [22] in place of σ-modification technique.

2) In the adaptation law (23), the partial derivative terms $\Theta_{W,i}$ for tuning all weights of the SRWNN can be evaluated by the backpropagation technique [13]. They can be found in [13].

Remark 2: In [17], the actual dynamics of the robots with uncertainties was only considered for designing the robust backstepping controller using NNs, where NNs were used to approximate the complicated nonlinear functions including the actual dynamics of the robot system. In this method, we cannot examine how much the dynamics of robot system is influenced by uncertainties. However, in the proposed method, since the dynamics of the biped robots expressed by (1) is designed separately by the nominal values and uncertainties, and SRWNNs are employed to observe the unknown uncertainties of dynamics of biped robots, we can establish the magnitude of the parametric uncertainty to show the robustness degree of the designed control system in the simulation procedure (see Table 1).

Remark 3: Compared with the previous control methods for the biped robot reported in [2-4], the proposed control method has the following advantages.

1) In [2] and [3], the SMC technique was applied to the robust control of the five-link and nine-link biped robot, respectively. These papers require the upper bounds of the internal uncertainties and external disturbances to compute the gains of the sliding controllers. However, it is difficult to satisfy this condition in the real bipedal systems because the exact values of the internal uncertainties and external disturbances are unavailable to measure or to know in advance. Therefore, the SMC method cannot be applied to the robust control of biped robot systems with the unknown uncertainties and disturbances. Hence, in the proposed control method, we employ the intelligent adaptive backstepping controller using the SRWNN uncertainty observer for the estimation of the uncertainty term of the bipedal systems. Accordingly, in our control system, any information for the model uncertainties and external disturbances is not needed.

2) In [4], the active force control method is applied to handle the external disturbance of the five-link biped robot efficiently. That is, the model uncertainties are not considered. However, in our control method, both the model uncertainties and external disturbances can be considered.

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

	m_i (Kg)		l_i (m)	d_i (m)	I_i
	Nominal	Actual	Nominal	Nominal	(Kgm ^{2})
LINK 1 (Right Toe)	0.6	$1.6\times\cos(t)$	0.1077	0.0828	1/6000
LINK 2 (Right Foot)	0.6	2.4	0.05	0.05	1/6000
LINK 3 (Right Leg)	4.550	$4.550\times\sin(t)$	0.502	0.267	0.105
LINK 4 (Right Thigh)	7.630	9.630	0.431	0.247	0.089
LINK 5 (Torso)	49	55	0.827	0.280	2.350
LINK 6 (Left Thigh)	7.630	9.630	0.431	0.247	0.089
LINK 7 (Left Leg)	4.550	9.10	0.502	0.267	0.105
LINK 8 (Left Foot)	0.6	1.2	0.05	0.05	1/6000
LINK 9 (Left Toe)	0.6	0.8	0.1077	0.0828	1/6000

4. COMPUTER SIMULATIONS

In this section, we examine our proposed IABC system for the tacking control of the nine-link biped robot shown in Fig. 2. The relative angle and the driving torque of the nine-link biped robot are defined as $\mathbf{q}=[q_0\ q_1\ \cdots\ q_8]$ and $\tau=[\tau_0\ \tau_1\ \cdots\ \tau_8]$, respectively. Here, the torque τ_0 at the toes of the supporting leg is zero because of the existence of one unpowered degree of freedom [3,5]. This aspect is the most important characteristic of the locomotion of the biped robot. Accordingly, it is assumed that each of the eight joints is driven by each independent motor. Also, the motion of the biped robot is assumed to be planned to start walking from the vertical position and walk steadily for several steps on a flat horizontal surface.

In this simulation, we derive a new walking pattern using a gait trajectory proposed in [5] for a stable walking of the nine-link biped robot. While the previous walking pattern shown in Fig. 3(a) represents that two legs gather after one step and this process is repeated, the proposed walking pattern shown in Fig. 3(b) describes the steady walking similar to the human walking. The dynamic model and kinematic model suggested in [3,5] are used in this simulation. Fig. 4 depicts the locomotion mode of the nine-link biped robot using the proposed walking pattern and the

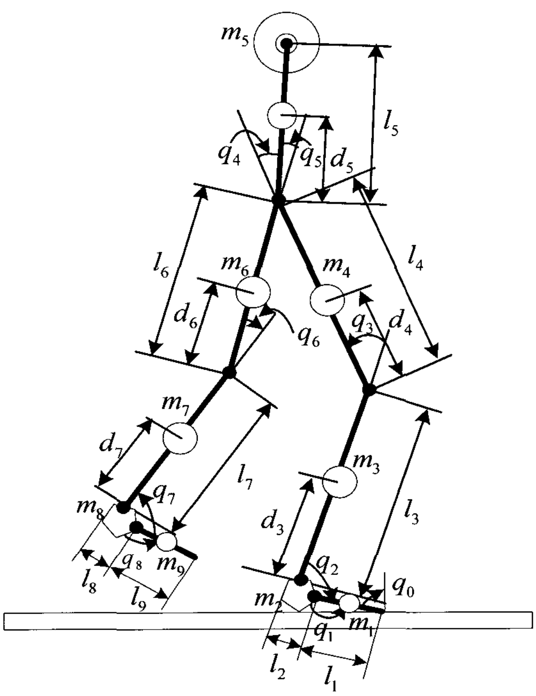
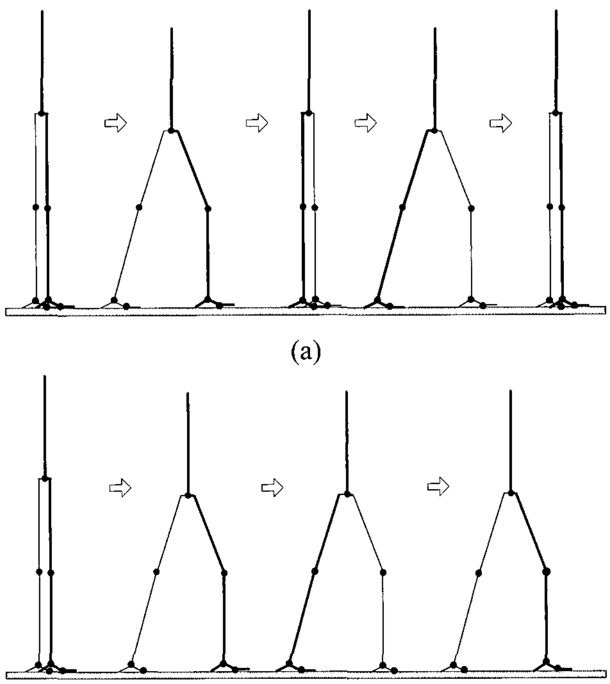


Fig. 2. The nine-link biped robot.



(a)

(b)

Fig. 3. The walking pattern of the nine-link robot (a) the pattern proposed in [2] (b) our proposed pattern.

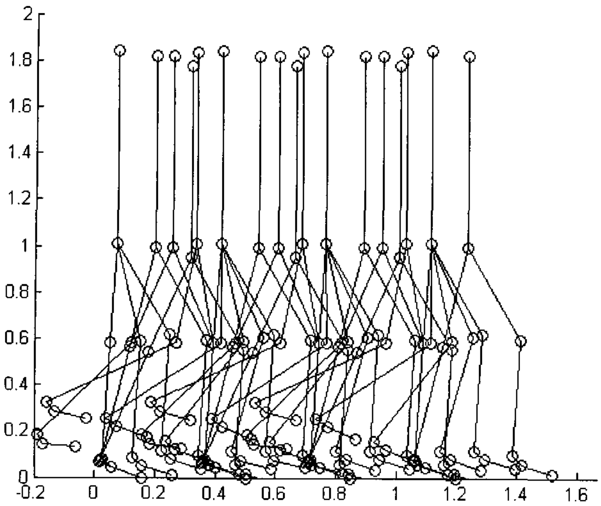


Fig. 4. The desired locomotion mode of the nine-link biped robot.

kinematic model. The change of the angular position of each joint to represent tshis walking pattern is defined as the reference trajectory. And to examine the robustness of the proposed control method, we compare the IABC method with the computed torque control (CTC) method.

Since q_0 of the biped robot model is the uncontrollable joint (i.e., $\tau_0 = 0$), our control law is redefined as follows:

$$\tau = \mathbf{M}(\mathbf{X}_1)\mathbf{U} + \mathbf{C}(\mathbf{X}_1, \mathbf{X}_2) + \mathbf{G}(\mathbf{X}_1) + \mathbf{F}(\mathbf{X}_2), \quad (36)$$

where $\mathbf{U} \in R^9$ is the vector with components

$$u_1 = -\frac{1}{M_{11}}\left[\sum_{l=1}^{8}(M_{1l+1}u_{l+1}) + C_1 + G_1 + F_1\right], \quad (37)$$

$$u_{l+1} = -\hat{\Gamma}_l(X_l \mid \hat{W}_l) - K_{1,l}\dot{Z}_{1,l} + \ddot{q}_{d,l} - K_{2,l}Z_{2,l} - Z_{1,l}. \quad (38)$$

Here, M_{1P} $(P = 1,2,...,9)$ denote the components of the first row of matrix $\mathbf{M}(\mathbf{X}_1)$ and C_1, G_1, and F_1 are the first element of the vectors $\mathbf{C}(\mathbf{X}_1, \mathbf{X}_2)$, $\mathbf{G}(\mathbf{X}_1)$, and $\mathbf{F}(\mathbf{X}_2)$, respectively. And to compare the performance of IABC system and CTC system, it is assumed that the same disturbances and uncertainties influence the biped robot system. The initial positions are set to $q_1(0) = q_8(0) = 1.92$, $q_2(0) = q_7(0) = 1.57$, and $q_h(0) = 0$ $(h = 3,...,6)$. That is, the nine-link biped robot is at initially upright posture. Also, the link masses m_i s of the biped robot are assumed to be uncertain. Especially, it is assumed that the masses m_1 and m_3 have the time-varying uncertainties, and m_2, m_7, and m_8 have about 200% uncertainties of the nominal values. The parameters of the nine-link biped robot are shown in Table 1. In addition, the external disturbances given by

$$\tau_d = [0.2sin(t) \;\; 0.5cos(2t) \;\; 0.7sin(3t) \;\; 0.6sin(2t) \;\; 0.3cos(t) \;\; 0.4sin(2t) \;\; 0.4sin(t) \;\; 0.2cos(t) \;\; 0.1sin(t)]^T$$

are injected into each joint of the biped robot. The control parameters of the IABC system for controlling the states from q_1 to q_8 are chosen as

$$\mathbf{K}_1 = diag[700 \;\; 300 \;\; 300 \;\; 500 \;\; 900 \;\; 900 \;\; 900 \;\; 900],$$
$$\mathbf{K}_2 = diag[200 \;\; 100 \;\; 100 \;\; 100 \;\; 100 \;\; 100 \;\; 200 \;\; 200],$$
$$\lambda = diag[0.01 \;\; 0.01 \;\; 0.01 \;\; 0.01 \;\; 0.01 \;\; 0.01 \;\; 0.01 \;\; 0.01],$$
$$\sigma = 0.001,$$

and the parameters for the CTC system are taken as

$$\mathbf{K}_P = diag[10000 \;\; 10000 \;\; 10000 \;\; 10000 \;\; 10000 \;\; 10000 \;\; 10000 \;\; 10000],$$
$$\mathbf{K}_D = diag[500 \;\; 500 \;\; 500 \;\; 500 \;\; 500 \;\; 500 \;\; 500 \;\; 500],$$

where $\mathbf{K}_P$ and $\mathbf{K}_D$ are the proportional and derivative gain 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 SRWNNs except d_{jk} and θ_{jk} are given randomly in the range of [-1 1]. $d_{jk} > 0$ and θ_{jk} are chosen in the range of [0 1] and as 0, respectively. That is, there are no feedback units initially. The inaccurate initial tuning parameters of the SRWNNs are trained optimally by online parameter tuning methodology. In Figs. 5 and 6, the actual joint angles of the IABC and the CTC system and their tracking errors are compared. These figures reveal that the proposed control system gives the excellent performance compared with the CTC system even under the influence of the time-varying uncertainties and external disturbances. Figs. 7, 8, and 9 show the SRWNN outputs, the L_2 norms of their estimated weights and the control torque signals, respectively. Note that the uncertainty terms $(\Gamma_l(\cdot))$ are observed by SRWNNs $(\hat{\Gamma}_l(\cdot))$, effectively. Besides, we can see that all signals such as joint angles, control torques, all weights of SRWNNs in the closed-loop system are bounded.

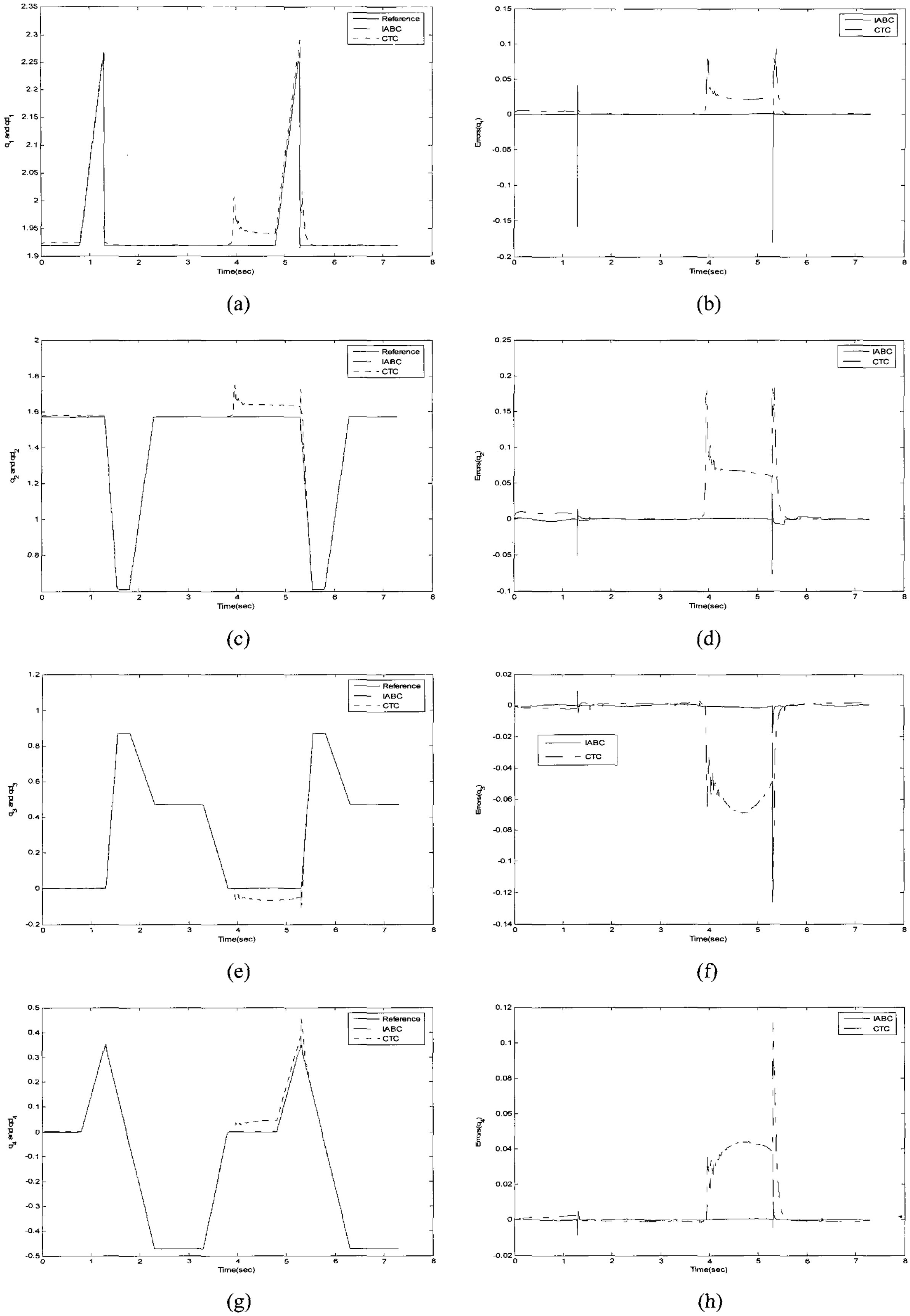


Fig. 5. The comparison of the control results and their errors (a) q_1 (b) the errors of q_1 (c) q_2 (d) the errors of q_2 (e) q_3 (f) the errors of q_3 (g) q_4 (h) the errors of q_4.

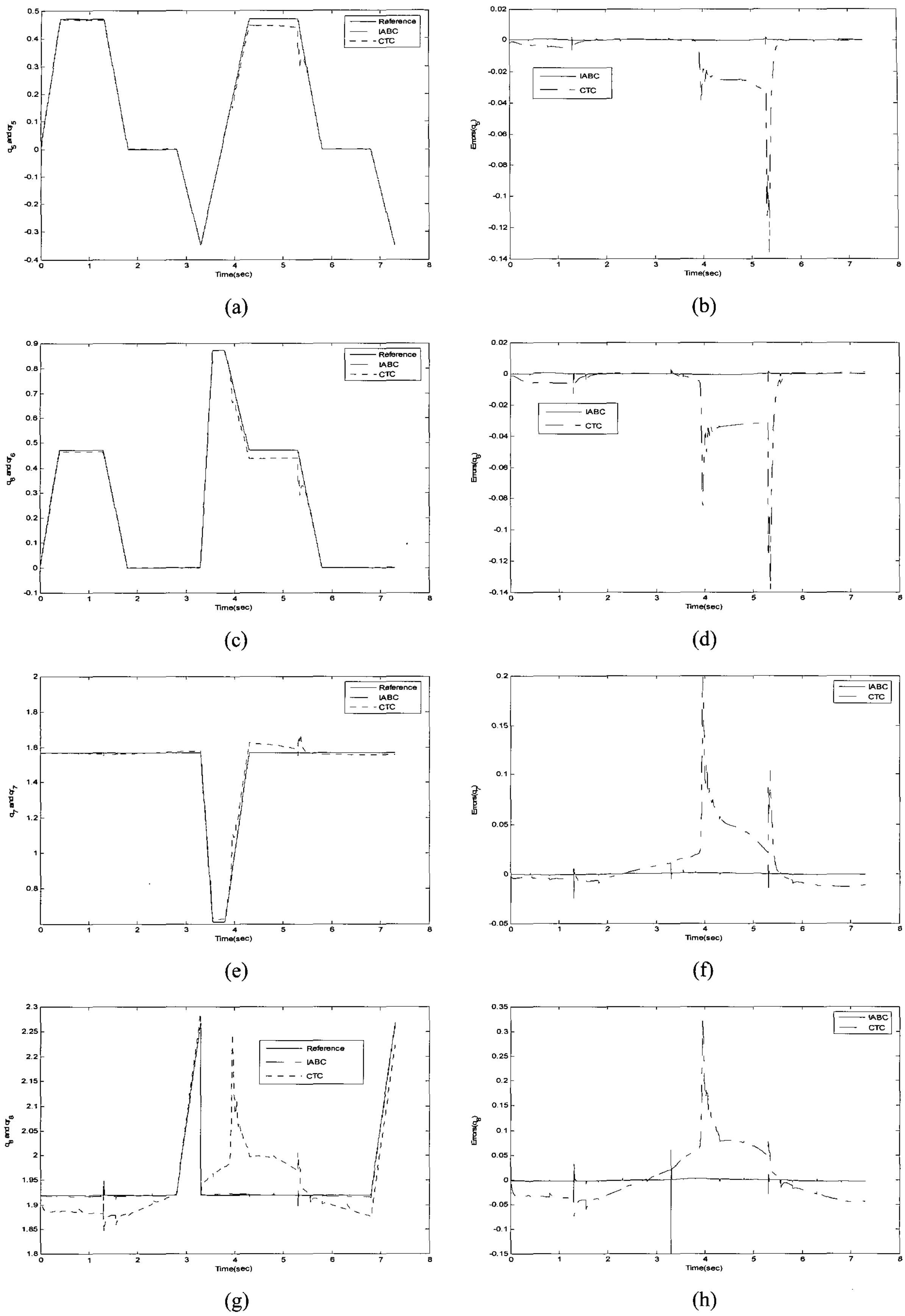
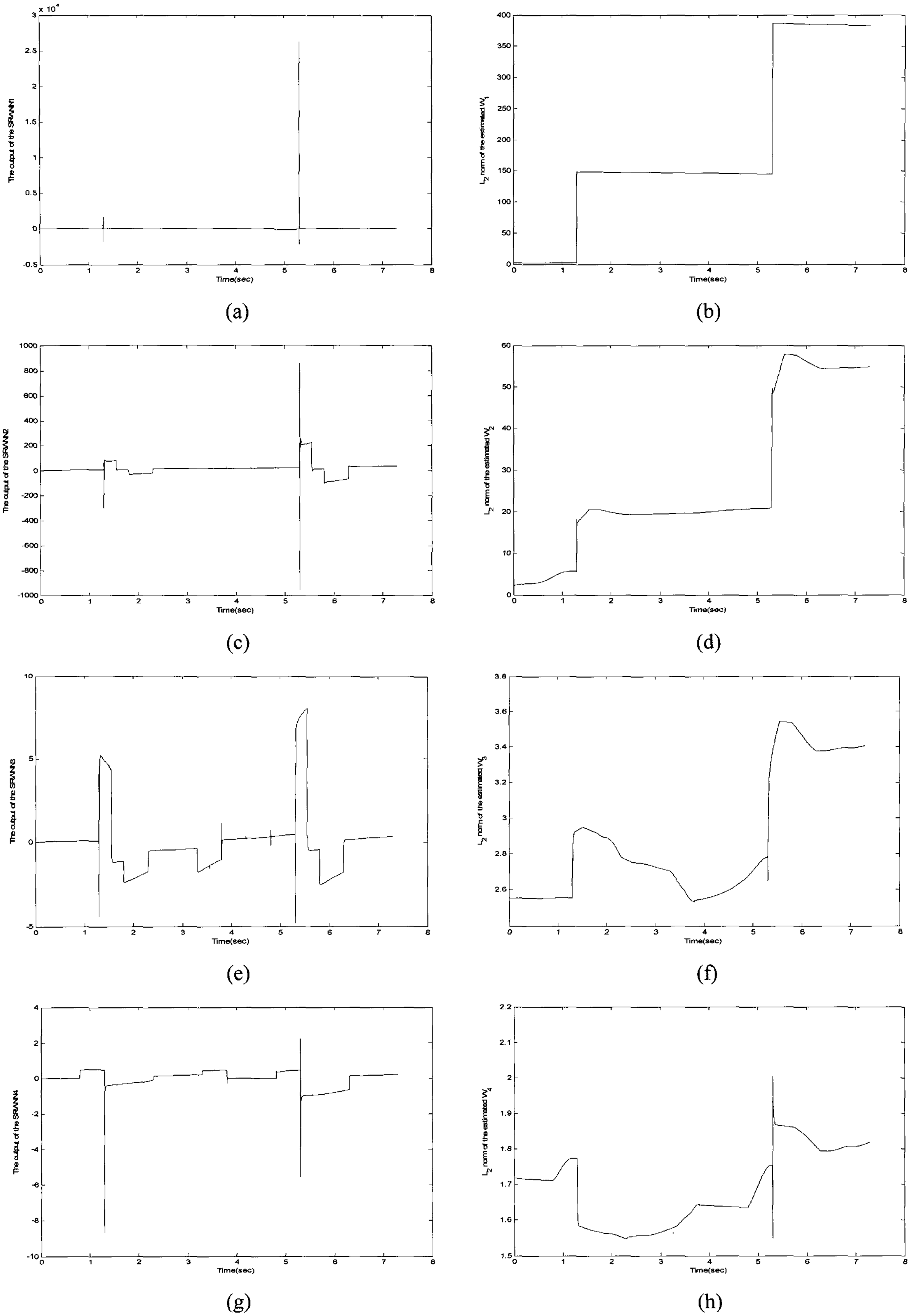


Fig. 6. The comparison of the control results and their errors (a) q_5 (b) the errors of q_5 (c) q_6 (d) the errors of q_6 (e) q_7 (f) the errors of q_7 (g) q_8 (h) the errors of q_8.



ig. 7. The SRWNN outputs and L_2 norm of their weights (a) SRWNN1 (b) L_2 norm of $\hat{W}_1$ (c) SRWNN2 (d) L_2 norm of $\hat{W}_2$ (e) SRWNN3 (f) L_2 norm of $\hat{W}_3$ (g) SRWNN4 (h) L_2 norm of $\hat{W}_4$.

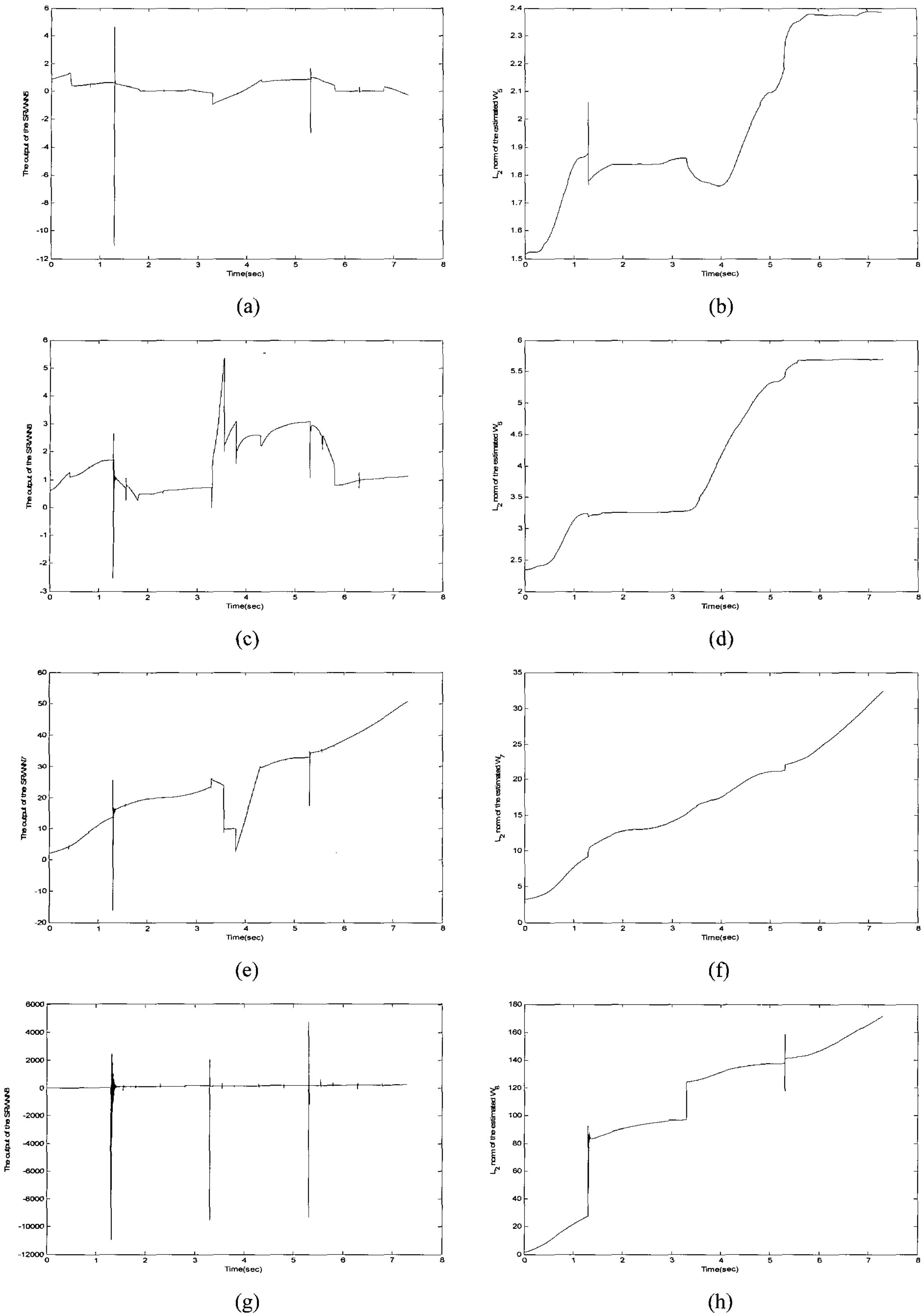
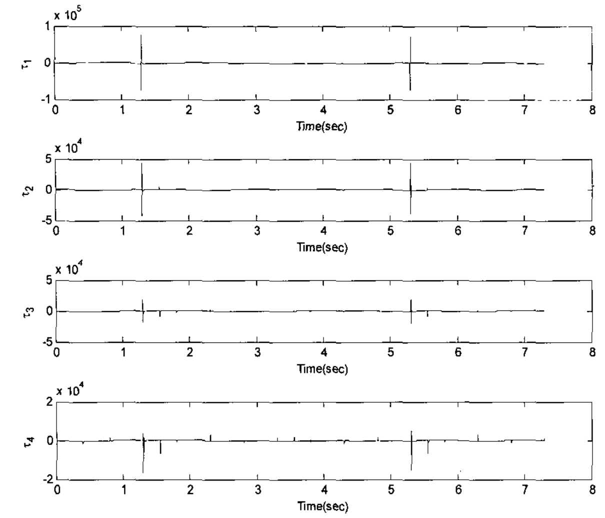
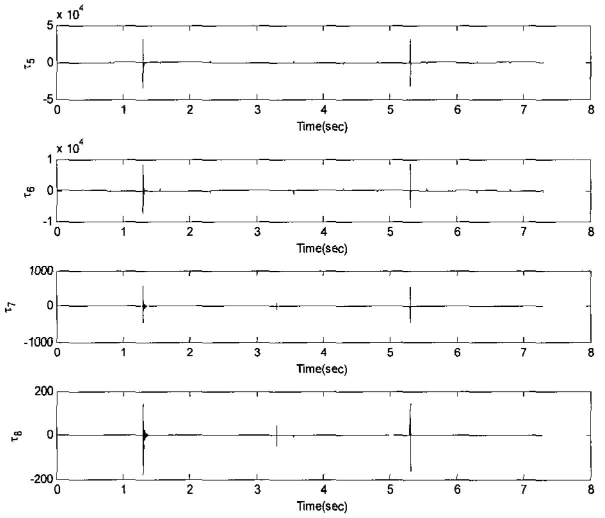


Fig. 8. The SRWNN outputs and L_2 norm of their weights (a) SRWNN5 (b) L_2 norm of $\hat{W}_5$ (c) SRWNN6 (d) L_2 norm of $\hat{W}_6$ (e) SRWNN7 (f) L_2 norm of $\hat{W}_7$ (g) SRWNN8 (h) L_2 norm of $\hat{W}_8$.



(a) $\tau_1 - \tau_4$



(b) $\tau_5 - \tau_8$

Fig. 9. Control torques.

5. CONCLUSIONS

In this paper, a robust control system using IABC technique for the biped robot with model uncertainties and external disturbances has been developed. First, the dynamics of the biped robots with model uncertainties has been introduced. Second, the robust control based on SRWNN uncertainty observer law has been designed for the stable walking control of biped robots. Third, from Lyapunov stability analysis, the adaptation laws for all weights of SRWNN have been derived, which have been used for guaranteeing that all signals in the closed-loop system are uniformly ultimately bounded. Finally, from the simulation results for a nine-link biped robot, it was shown that the proposed control system has the excellent tracking performance and the robustness against model uncertainties and external disturbances.

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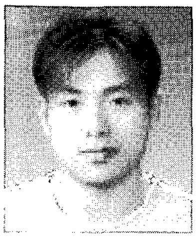

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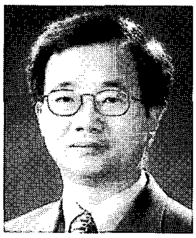

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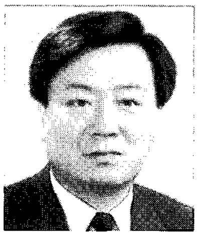

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