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Robust adaptive backstepping control for a class of nonlinear systems using recurrent wavelet neural network

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ABSTRACT

This paper develops a robust adaptive backstepping control (RABC) algorithm for a class of nonlinear systems using a recurrent wavelet neural network (RWNN). This RABC comprises an RWNN controller and a robust controller. The RWNN controller is the main tracking controller utilized to mimic an ideal backstepping control law; and the parameters of RWNN are tuned on-line by adaptation laws derived from the Lyapunov stability theorem and gradient descent method. The robust controller is employed to suppress the influence of approximation error between the RWNN controller and the ideal backstepping control law, so that robust tracking performance of the system can be achieved. Finally, the proposed control method is applied to resolving the marine course-changing and gyros synchronization control problems. Simulation results verify that the proposed control algorithm can achieve favorable tracking performance of these nonlinear systems. Comparison with a wavelet adaptive backstepping control (WABC) and a robust adaptive backstepping control (RABC) partially tuned with adaptation laws demonstrates that the proposed RABC fully tuned with adaptation laws can achieve better control performance than the other two control methods.

1. Introduction

In recent years, neural networks (NNs) have been widely used for identification and control of dynamic systems [1–8]. Many studies have suggested NNs as powerful building blocks for a wide class of complex nonlinear system control strategies when no complete model information is available or even when a controlled plant is considered as a "black box". The most useful property of NNs is their approximation ability, in that they can approximate any function with an arbitrary degree of accuracy. Moreover, according to the structure, NNs can be mainly classified as feed-forward neural networks (FNNs) [1–5] and recurrent neural networks (RNNs) [6–8]. As known, FNNs represent a static mapping. Without the aid of tapped delays, FNNs are unable to represent a dynamic mapping. Moreover, the weight update of FNNs does not utilize internal network information and the function approximation is sensitive to the training data. As to RNNs, of particular interest is their ability to deal with time-varying inputs or outputs through their own natural temporal operation [6]. Thus, RNNs represent a dynamic mapping and demonstrates good control performance in the presence of un-modeled dynamics [7,8]. The basic concepts in neural network-based feedback control methods are to provide online learning algorithms that do not require preliminary offline tuning. Some of these online learning algorithms are developed from the back-propagation learning algorithm [1,4,6] and some are derived from the Lyapunov stability theorem [2,7,8].

In recent years, a number of studies have been conducted on the applications of wavelet neural networks (WNNs), which combine the learning ability of NNs and the capability of wavelet decomposition [9–15]. Unlike the sigmoidal functions used in conventional neural networks, wavelet functions are spatially localized, so that the learning capability of WNN is more efficient than the conventional sigmoidal function neural network for system identification and control. The training algorithms for WNN typically converge in a smaller number of iterations than those for conventional NNs [9]. Thus, WNN has been proved to be better than the Gaussian-type neural network in that the structure can provide more potential to enrich the mapping relationship between inputs and outputs [10]. There has been considerable interest in exploring the applications of WNN to dealing with nonlinearity and uncertainties of control systems [11–14]. In [15], a simple WNN structure has been developed and is used as an identifier to approximate the dynamics of an

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Nomenclature

$d(t)$	Unknown external disturbance
$e_1(t), e_2(t)$	Tracking error
H_∞	Tracking performance
$L_1(t), L_2(t)$	Lyapunov functions
m_{ij}	Translation factor
N_i	Number of the input variables
N_p	Total number of the node in the product layer
r_{ij}	Recurrent weight
$u(t)$	Control input of the system
$u^*_{IBC}(t)$	Ideal backstepping control law
$\hat{u}_{RWNN}$	RWNN controller
u_{RC}	Robust controller
$\tilde{u}(t)$	Estimation error
v_{ij}	Dilation factor
$\boldsymbol{w},\boldsymbol{m},\boldsymbol{v},\boldsymbol{r}$	Parameters of the connection weights and mother wavelets
$\boldsymbol{w}^*$	Optimal constant parameter of $\mathbf{w}$
$x, \dot{x}, \ddot{x}$	Joint position, velocity and acceleration
$x_d, \dot{x}_d, \ddot{x}_d$	Desired joint position, velocity and acceleration
$y_{ij}^{(2)}$	Output of mother wavelet node
$y_o^{(4)}$	Output of RWNN
$y_i^{(1)}$	The *i-th* input to the node of input layer
$y_i^{(2)}$	The *i-th* input to the node of mother wavelet layer
$z_i^{(3)}$	The *i-th* input to the node of product layer
$z_j^{(4)}$	The *j-th* input to the node of output layer
t_m	Time constant (s)
$\alpha(\cdot)$	Unknown but bounded real continuous function
α_0	Nominal value of $\alpha(\cdot)$
$\beta(\cdot)$	Unknown but bounded real continuous function
β_0	Nominal value of $\beta(\cdot)$
$\varepsilon(t)$	Lumped uncertainty
$\psi(t)$	Ship heading angle
ρ	Prescribed attenuation constant
ϑ	Approximation error
$\phi(\xi)$	Gaussian function
ϕ_{Tij}	Output through delay sampling time T
$\sigma(t), \dot{\sigma}(t)$	Stabilizing functions
λ_1, λ_2	Positive constants
$\kappa_1, \kappa_2, \kappa_3, \kappa_4$	Learning-rates

unknown system. With this approach, its applications are limited to the control systems with unity input gain. Nevertheless, the major drawback of the aforementioned WNNs is that their application domain is limited to static problem due to its feed-forward network structures [9–15]. Compared with [15], this study develops a more general recurrent WNN (RWNN) for use as the main controller to track desired trajectory; and its applications can be a more general nonlinear control system.

In the past decade, many researchers have been devoted to the backstepping control for the uncertain nonlinear systems [16–20]. This control technique can be effectively employed to linearize a nonlinear system in the presence of uncertainties, and it is a systematic and recursive design methodology. The basic idea of backstepping control design method is to select recursively some appropriate functions of state variables as pseudo-control inputs for subsystems of lower dimension in the overall system. Each backstepping stage results in a new pseudo-control design, expressed in terms of the pseudo-control design from preceding design stages. The procedure terminates a feedback design for the true control input, which achieves the original design objective by virtue of a final Lyapunov function formed by summing the Lyapunov functions associated with each individual design stage [18].

Robust control techniques have been used when the system is subject to bounded uncertainty with unknown upper bound. According to this observation, some robust adaptive fuzzy control approaches have been proposed to attenuate the effects of approximation error to a desired prescribed level [21,22]. This proves that the robust control schemes are suitable for solving the approximation errors of WNNs.

Over and above these motivations, a RWNN control system is proposed in this study, involving dynamic elements in the form of feedback connections that are used as internal memories, to achieve robust adaptive backstepping control. This control system comprises two parts: a RWNN controller utilized as the main tracking controller to mimic an ideal backstepping control law, and a robust controller employed to suppress the influence of approximation error between the RWNN controller and the ideal backstepping control law. The adaptive laws of the control system are derived from the Lyapunov stability theorem and gradient descent method. Thus, the stability of the system can be guaranteed. In this control system design, knowledge of the precision dynamic models of the controlled plant is not required. Finally, the proposed RABC is applied to resolving the marine course-changing and gyros synchronization control problems to demonstrate its effectiveness.

The remainder of this study is organized as follows. System description and ideal backstepping control law are presented in Section 2. Section 3 describes the architecture of RWNN. Section 4 introduces the RABC scheme. In Section 5, simulation results for two nonlinear systems are presented to verify the effectiveness of the proposed control method. Finally, Section 6 offers concluding remarks.

2. System description and ideal backstepping control law

Consider a class of second-order nonlinear systems expressed in the following form:

$$\ddot{x}(t) = \alpha(x(t), \dot{x}(t)) + \beta(x(t), \dot{x}(t))u(t) + d(t) \tag{1}$$

where $\alpha(\cdot)$ and $\beta(\cdot)$ are unknown but bounded real continuous functions, $u(t) \in \Re$ is the control input; $d(t) \in \Re$ is an unknown external disturbance, and $\underline{\mathbf{x}}(t) = [x(t), \dot{x}(t)]^T \in \Re^2$ is a state vector of the system assumed to be available for measurement. For the system to be controllable, it is required that $\beta(\underline{\mathbf{x}}(t)) \neq 0$ for all $\underline{\mathbf{x}}$ in a certain controllability region $U_c \in \Re^2$. Since $\beta(\underline{\mathbf{x}}(t))$ is continuous, without loss of generality, it is assumed that $\beta(\underline{\mathbf{x}}(t)) > 0$ for all $\underline{\mathbf{x}} \in U_c$.

In case that all the parameters of the system are well known, the nominal model of the nonlinear systems (1) can be represented as

$$\ddot{x}(t) = \alpha_0(\underline{\mathbf{x}}(t)) + \beta_0 u(t) \tag{2}$$

where $\alpha_0(\underline{\mathbf{x}}(t))$ is the nominal value of $\alpha(\underline{\mathbf{x}}(t))$ and $\beta_0$is a nominal constant of $\beta(\underline{\mathbf{x}}(t))$. If external disturbance and uncertainties exist, the nonlinear systems (1) can be reformulated as

$$\begin{aligned}\ddot{x}(t) &= [\alpha_0(\underline{\mathbf{x}}(t)) + \Delta\alpha(\underline{\mathbf{x}}(t))] + [\beta_0 + \Delta\beta(\underline{\mathbf{x}}(t))]u(t) + d(t) \\ &= \alpha_0(\underline{\mathbf{x}}(t)) + \beta_0 u(t) + \varepsilon(t)\end{aligned} \tag{3}$$

where $\Delta\alpha(\underline{\mathbf{x}}(t))$ and $\Delta\beta(\underline{\mathbf{x}}(t))$ denote the uncertainties; $\varepsilon(t)$ is called the lumped uncertainty, defined as $\varepsilon(t) \equiv \Delta\alpha(\underline{\mathbf{x}}(t)) + \Delta\beta(\underline{\mathbf{x}}(t))u(t) + d(t)$.