Neural Network Based Model Reference Adaptive Control for Ship Steering System

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Abstract

A neural network-based model reference adaptive control approach (MRAC) for ship steering systems is proposed in this paper. For the nonlinearities of ship steering system, performances of traditional adaptive control algorithms are not satisfactory in fact. The presented MRAC system utilizes RBF neural network to approximate the unknown nonlinearities in order to get a high adaptive control performance. Mechanism and stability of the control system are presented in detail. Also, a stable controller parameter adjustment law for RBF neural network, which is determined by using Lyapunov stability theory, is constructed. Simulation also shows the effectiveness and high performance of the proposed algorithm.
Keyword: neural network, model reference adaptive control, ship steering.

I. Introduction

To improve fuel efficiency and reduce wear on ship components, autopilot systems have been developed and implemented for controlling the directional heading of ships [1]. Often, the autopilots utilize simple control schemes such as PID control. However, the capability for manual adjustments of the parameters of the control is desired to compensate for disturbances imposing on the ship such as wind, wave and currents. For large variations, the parameters of the autopilot must be continually modified. Such continual adjustments are necessary because the dynamics of a ship varies with, for example, speed, trim, and loading. As a result, it is of great interest to have an adaptive controller for automatically adjusting of the control law.

Since MRAC is first applied to ship steering control system in 1970s by Amerongen, many adaptive algorithms for ship steering control are available in the literature [2-3]. However, as a result of being based on linear dynamic model of ship steering, the performance of these algorithms are not satisfactory.

Neural network thus appears to offer advantages over other forms of control for ship steering, in which the outstanding nonlinear mapping capability of neural network is exploited for forward and inverse plant models in order to develop different adaptive control schemes [4-5]. In this paper, a neural network-based model reference adaptive controller is developed, in which the error between the outputs of the plant and the reference model is used to adapt the controller parameters. The nonlinear part of the controller, which compensates the plant nonlinearity, is implemented by an

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RBF network. The adjustment mechanism is determined by the Lyapunov stability analysis of the overall adaptive control system. This kind of neural network-based adaptive controller is applicable to a wide variety of practical problems.

The paper is organized as follows: Section 2 presents the nonlinear dynamic model of ship steering used in this study and gives an overview of the neural network-based MRAC system. In section 3, the stability of the proposed control system is analyzed. In section 4, numerical simulation is made to demonstrate the control performance of neural network-based MRAC system. Conclusions are summarized in section 5.

II. Ship Steering Control

A. *Nonlinear Model of Ship Steering*

Generally, ship dynamics is obtained by Newton's laws of motion [6-8]. The SISO maneuvering Model of a ship may be expressed as

$$\ddot{\psi} + kd(\dot{\psi}) = k\delta \ , \qquad (1)$$

where $\psi(t)$ is the yaw angle of the ship, δ is the rudder angle and $d(\dot{\psi})$ is a damping term of the form

$$d(\dot{\psi}) = d_3\dot{\psi}^3 + d_2\dot{\psi}^2 + d_1\dot{\psi} + d_0 \ . \qquad (2)$$

Because of symmetry, most ship have the property that $d_0 = d_2 = 0$. Shown from (1) and (2), ship exhibits nonlinear dynamical relations between its heading and rudder angle.

Model reference adaptive control algorithm is one of most effective methods applied to ship steering system for its capability of adaptiveness and robustness. The dynamics of the reference model should be matched to the dynamics of the ship regardless of the magnitude of the demanded change of reference yaw angle. An appropriate model proposed by Van Amerongen is as follows [2]:

$$\ddot{\psi}_m + a_m\dot{\psi}_m + b_m\psi_m = k_m\psi_r \ , \qquad (3)$$

where ψ_m specifies the desired system performance for the ship heading (yaw angle) ψ.

B. *Neural Network-based MRAC System*

The objective of a MRAC system is to obtain a control law and an updating law of the controller parameters, such that the overall control system responds dynamically as the specified reference model. This may be expressed as follows. The objective is to determine a control action law $\delta(t)$, for all $t > 0$, and an updating law of the controller parameters such that

$$\lim_{t\to\infty}\left|\psi(t) - \psi_m(t) \le \varepsilon\right| \qquad (4)$$

for some specified constant $\varepsilon > 0$.

The nonlinear adaptive control system considered in the present paper is generalized from the well-known linear model reference adaptive control systems [9-10]. Consider the plant to be controlled given by (1) and reference model given by (2). Assume that a_m, b_m, k_m have been chosen such that a desired trajectory $\psi_m(t)$ is obtained for the plant output $\psi(t)$ to follow. The system structure is shown in Fig. 1.

The proposed control law has the following form:

$$\delta(t) = \frac{1}{k}\left(-b_m\psi(t) - a_m\dot{\psi}(t) + k_m\psi_r(t) + N_f\left[\dot{\psi}, w(t)\right]\right) \ , \qquad (5)$$

where $N_f(\dot{\psi}, w) = \sum_i^n w_i \exp\left(-\frac{\left|\dot{\psi} - c_i\right|^2}{2\sigma_i^2}\right)$ is implemented using an RBF network that approximates the function of $d(\cdot)$. w is the parameter vector of the neural network, which represents the neural network-based adaptive controller parameters to be tuned.

Define the error signal as

$$e(t)=\psi(t)-\psi_m(t) \ . \qquad (6)$$

When the neural network exactly represents the function $d(\cdot)$, i.e., when $N_f(\dot{\psi}(t),w)=d(\dot{\psi}(t))$ for all *t*, the closed loop system equation, in terms of the error signal, is obtained by substituting (2) and (5) into (1) as

$$\ddot{e}(t)+a_m\dot{e}(t)+b_m e(t)=0 \ , \qquad (7)$$

which is asymptotically stable for $a_m>0$ and $b_m>0$. So, the control objective of $\psi(t)$ tracking $\psi_m(t)$ is achieved, i.e., $e(t)=\psi(t)-\psi_m(t)\to 0$ as $t\to\infty$.
Consider the neural network learning error, i.e., the approximation error in the representation of the function $d(\cdot)$ by the neural network, given by
Substitute (3), (5) and (8) into (1), the closed loop system equation becomes

$$\Delta(\dot{\psi},w)=N_f[\dot{\psi}(t),w(t)]-d(\dot{\psi}(t)) \ . \qquad (8)$$

Note that when the learning error tends to zero, i.e., when $N_f\to d$, the control error $e(t)$ tends to zero too. Define the neural network weight parameter error as $\tilde{w}=w-w^*$, where w^* is optimal parameter vector corresponding to the global minimum error of the network which minimizes $|\Delta(\dot{\psi},w)|$; i.e., the minimum value of $|\Delta(\dot{\psi},w)|$ that could be reached is $|\Delta(\dot{\psi},w^*)|$.

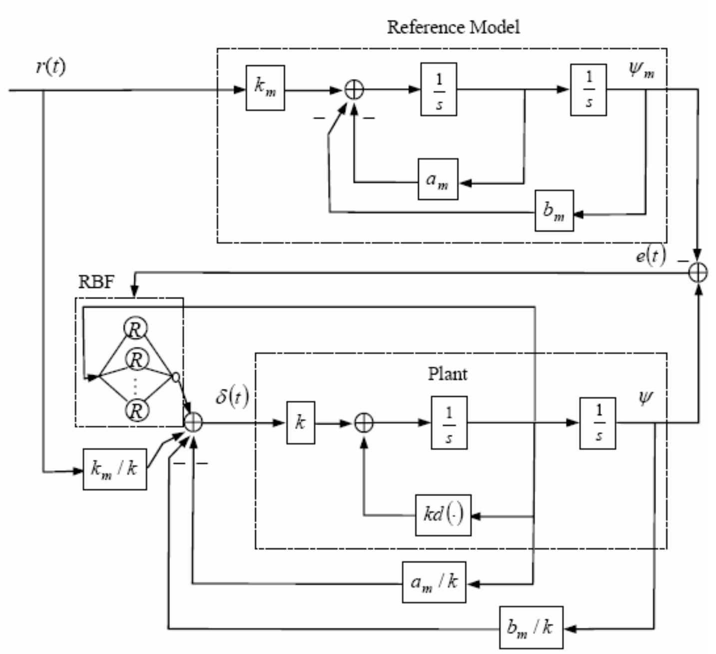

Fig. 1. Neural network-based model reference adaptive control system structure

III. Stability Analysis

It is assumed that both RBF centers and widths have been chosen and fixed adequately. To drive the ship responding dynamically as the specified reference model, the weight values of the linear combiner will be adjusted by a learning law so to force the error $|\Delta(\dot{\psi},w)|$ tend towards to minimum value. For the error between the output of the actual nonlinear function $d(\cdot)$ and the output of designed RBF neural network is not available, an alternative approach by using the error between the reference model output and the plant output as the activation signal of the parameter adjusting law is proposed. In this subsection, analysis will be given for the stability of the parameter adjusting law. Background material on practical stability will be first introduced [11].

Lemma 1.: Let a system be given by

$$\dot{x} = f(x,t), \qquad t > 0 \ , \tag{9}$$

which has the equilibrium state at the origin, i.e., $f(0,t) = 0$ for all $t \geq 0$. Let the perturbed system be given by

$$\dot{x} = f(x,t) + p(x,t) \ . \tag{10}$$

Let *Q* be a set which is closed and bounded containing the origin and let Q_0 be a subset of *Q*. Let $x(t, x_0, t_0)$ be the solution of (11) satisfying $x(t_0, x_0, t_0) = x_0$. Let *P* be the set of perturbations satisfying $|p(x,t)| \leq \delta$ for all *x*, where $\delta > 0$. If for each *p* in *P*, each x_0 in Q_0, and each $t_0 \geq 0$, $x(t, x_0, t_0)$ is in *Q* for all $t \geq 0$, then, the equilibrium of (10) at the origin is said to be *practically stable*.

Lemma 2.: Let $V(x)$ be a scalar function which has continuous first partial derivative for all *x* and with the property that $V(x) \to \infty$ as $|x| \to \infty$. Let $\dot{V}(x)$ denote the time derivative of *V* along the solutions of system (11). If $\dot{V}(x) \leq -\varepsilon$ for all *x* outside Q_0, for all *p* in *P*, and for all $t \geq 0$ and if $V(x) \leq V(y)$ for all *x* in Q_0, and all *y* outside *Q*, then system (10) possesses *strong practical stability*.

Based on **Lemma 1** and **2,** a theorem is proposed as follows.

Theorem 1. Suppose that the control law is given by (5) and the parameter updating law is given by

$$\dot{w}(t) = -\Psi B(t)\dot{e}(t) - Kw(t) \ , \tag{11}$$

where $w \in R^p$ is the weight factor of the linear combiner of the RBF units; Ψ and *K* are diagonal positive definite matrices, i.e., $\Psi = diag(\Psi_i)$ and $K = diag(K_i)$ with $\Psi_i > 0$ and $K_i > 0$; $B(t) \in R^p$ is the output of the hidden layer of the RBF, i.e., $N_f[\dot{\psi}(t), w(t)] = B^T(t)w(t)$. Then, the whole system given by

$$\begin{cases} \ddot{e}(t) + a_m \dot{e}(t) + b_m e(t) = 0 \\ \dot{\tilde{w}}(t) = -\Psi B(t)\dot{e}(t) - Kw(t) \end{cases} \tag{12}$$

possesses strong practical stability under perturbation given by $|\Delta(\dot{\psi}, w)|$, where $\tilde{w}(t) = w(t) - w*$ and $w*$ is the optimal parameter vector as defined before.

Proof: System (13) under the given perturbation is described by

$$\begin{cases} \ddot{e}(t) + a_m \dot{e}(t) + b_m e(t) = \Delta(\dot{\psi}, w) \\ \dot{\tilde{w}}(t) = -\Psi B(t)\dot{e}(t) - Kw(t) \end{cases} . \tag{13}$$

Consider the positive definite function

$$V(e, \tilde{w}) = \frac{1}{2} b_m e^2 + \frac{1}{2} \dot{e}^2 + \frac{1}{2} \tilde{w}^T \Psi^{-1} \tilde{w} \ . \tag{14}$$

Clearly, *V* can be upper bounded by

$$V(e, \tilde{w}) \leq \frac{1}{2} b_m e^2 + \frac{1}{2} \dot{e}^2 + \frac{1}{2} \left\|\Psi^{-1}\right\| \cdot \left\|\tilde{w}\right\|^2 \ . \tag{15}$$

The time derivative of V evaluated along the trajectories of system (13) is

$$\dot{V}_{(13)} = b_m e\dot{e} + \dot{e}\ddot{e} + \tilde{w}^T \Psi^{-1} \dot{\tilde{w}} = -a_m \dot{e}^2 + \Delta(\dot{\psi}, w)\dot{e} + \tilde{w}^T \Psi^{-1} \dot{\tilde{w}} \ . \tag{16}$$

Since both $d(\dot{\psi})$ and $N_f[\dot{\psi}, w]$ are continuously differentiable with respect to their arguments, so $\Delta(\dot{\psi}, w)$ is continuously differentiable too. One can apply the mean value theorem and obtain

$$\Delta(\dot{\psi}, w) = \Delta(\dot{\psi}, w*) + \tilde{w}^T \left(\frac{\partial \Delta(\dot{\psi}, w_\xi)}{\partial w_\xi} \right) \tag{17}$$

for some w_ξ, where $\Delta(\dot{\psi}, w^*)$ is the learning error evaluated at the global minimum $w = w^*$. Considering (8) and

$$\frac{\partial \Delta(\dot{\psi}, w_\xi)}{\partial w_\xi} = \frac{\partial N_f(\dot{\psi}, w_\xi)}{\partial w_\xi} = B(t)$$

and substituting (18) into (17), one gets

$$\dot{V}_{(13)} = -a_m \dot{e}^2 + \Delta(\dot{\psi}, w^*)\dot{e} + \tilde{w}^T\left(B\dot{e} + \Psi^{-1}\dot{\tilde{w}}\right). \qquad \textbf{(18)}$$

The second term of (18) is partially cancelled out by the following parameter updating law

$$\dot{\tilde{w}}(t) = -\Psi B(t)\dot{e}(t) - Kw(t). \qquad \textbf{(19)}$$

As w^* is a constant vector, he adjusting law of w can be determined as in (9), i.e.,

$$\dot{w}(t) = -\Psi B(t)\dot{e}(t) - Kw(t).$$

Then, Considering (20) and $\tilde{w}(t) = w(t) - w^*$, (14) becomes

$$\dot{V}_{(13)} = -a_m \dot{e}^2 + \Delta(\dot{\psi}, w^*)\dot{e} - \tilde{w}^T \Psi^{-1} K\tilde{w} - \tilde{w}\Psi^{-1}Kw^*,$$

and $\dot{V}_{(13)}$ can be upper bounded by

$$\dot{V}_{(13)} \le -a_m \dot{e}^2 + \left|\Delta(\dot{\psi}, w^*)\right| \cdot |\dot{e}| - \mu_1 \|\tilde{w}\|^2 - \mu_2 \|\tilde{w}\| \cdot \|w^*\|, \qquad \textbf{(20)}$$

where $\mu_1 = \min_i\{K_i / \Psi_i\}$ and $\mu_2 = \left|\Psi^{-1}K\right|$. Taking into account the fact that the bilinear terms can be expressed as

$$\left|\Delta(\dot{\psi}, w^*)\right| \cdot |e| = -\frac{1}{2}\left(\frac{|e|}{\eta} - \Delta(\dot{\psi}, w^*)\eta\right)^3 + \frac{1}{2}\frac{e^2}{\eta^2} + \frac{1}{2}\eta^2\left|\Delta(\dot{\psi}, w^*)\right|^2, \qquad \textbf{(21)}$$

and

$$\|\tilde{w}\| \cdot \|w^*\| = -\frac{1}{2}\left(\frac{\|\tilde{w}\|}{\xi} - \|w^*\|\xi\right)^3 + \frac{1}{2}\frac{\|\tilde{w}\|^2}{\xi^2} + \frac{1}{2}\xi^2\|w^*\|^2 \qquad \textbf{(22)}$$

for some $\eta \in R$ and $\xi \in R$, (21) can be rewritten as

$$\dot{V}_{(13)} \le -\left(a_m - \frac{1}{2\eta^2}\right)\dot{e}^2 - \left(\mu_1 - \frac{\mu_2}{2\xi^2}\right)\|\tilde{w}\|^2 + \frac{1}{2}\left(\eta^2\left|\Delta(\dot{\psi}, w^*)\right|^2 + \mu_2\xi^2\|w^*\|^2\right) \qquad \textbf{(23)}$$

Equivalently, (24) can be written as

$$\dot{V}_{(13)} \le -\sigma V + \rho \qquad \textbf{(24)}$$

with

$$\sigma = \min\left(2a_m - \frac{1}{\eta^2}, \frac{2\mu_1\xi^2 - \mu_2}{\left\|\Psi^{-1}\right\| \cdot \xi^2}\right),$$

and $\rho = \frac{1}{2}\left(\eta^2\left|\Delta(\dot{\psi}, w^*)\right|^2 + \mu_2\xi^2\|w^*\|^2\right)$. It is always possible to choose $\eta^2 > (1/2a_m)$ and $\xi^2 > (\mu_2 / 2\mu_1)$, i.e., $\sigma > 0$. Now, consider

$$Q = Q_0 = \left\{(e, \tilde{w}) : V(e, \tilde{w}) \le \frac{\rho + \varepsilon}{\sigma}\right\}$$

for some $\varepsilon > 0$. It results from (25) that $\dot{V}_{(13)} < -\varepsilon$ for all *e* and $\tilde{w}$ outside *Q* since

$$V(e,\tilde{w}) > \frac{\rho+\varepsilon}{\sigma}$$

and that $V(x) < w(y)$ for all $x \in Q$ and all y outside Q. Then apply Lemma 2, (25) implies that (13) possess strong *practical stability*.

IV. Simulation Result

To show the performance of the proposed neural network-based model reference adaptive control algorithm, and also to verify the stability proved in the preceding theoretical analysis, numerical simulation is carried out for a ship steering system.
The dynamics model of a ship steering system is given as

$$k = 0.0107, d_1 = 9.42, d_3 = 2.24 \ ,$$

which corresponds to the dynamics of a warship traveling at 16 knots [12]. Define the reference model (3) as

$$k_m = 0.025, a_m = 0.45, b_m = 0.025 \ .$$

RBF network is defined with

$$\begin{aligned} c &= [-0.5 \quad -0.25 \quad 0.25 \quad 0.5] \\ \sigma &= [10 \quad 10 \quad 10 \quad 10] \\ w(0) &= [0 \quad 0 \quad 0 \quad 0] \end{aligned} \ ,$$

and

$$\begin{aligned} \Psi &= diag[19.9 \quad 19.9 \quad 19.9 \quad 19.9] \\ K &= diag[0.05 \quad 0.05 \quad 0.05 \quad 0.05] \end{aligned} \ .$$

After the training process is completed, $|\Delta(\dot{\psi}, w)| = 0.0025$ and $w(t) = [0.6292 \quad -0.8088 \quad -0.0572 \quad -0.2986]$. The evolution of the desired and measured output signals of the system is presented in Fig.2. The learning process can be seen in Fig.3 and Fig.4, which represents respectively the error between the reference model and the plant and the learning error of the RBF neural network. Results show that the proposed neural network-based MRAC algorithm and the updating law have satisfactory performance.

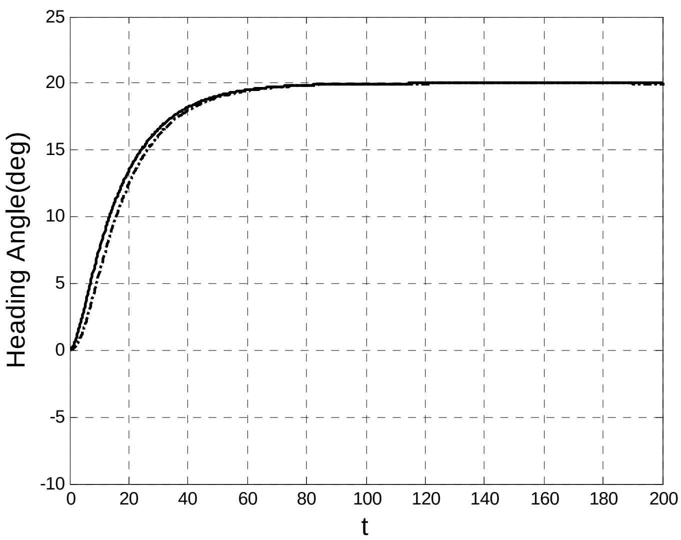

Fig. 2. Desired output of reference model and measured output of plant (*dashed line*)

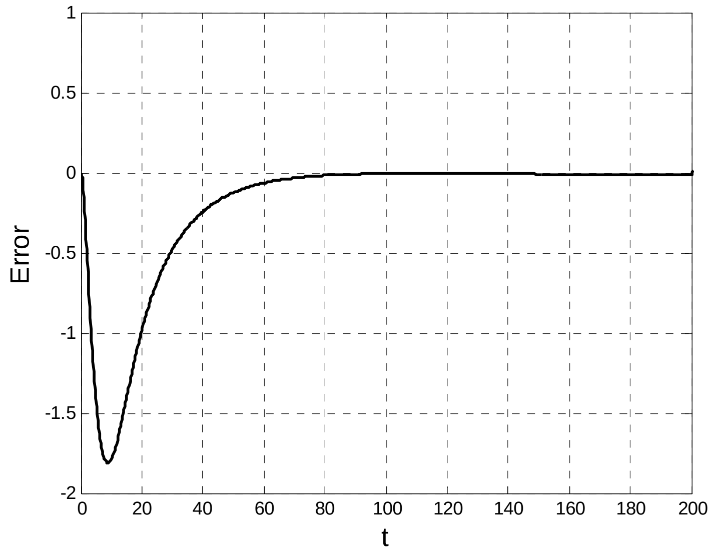

Fig. 3. Error between the reference model and the plant

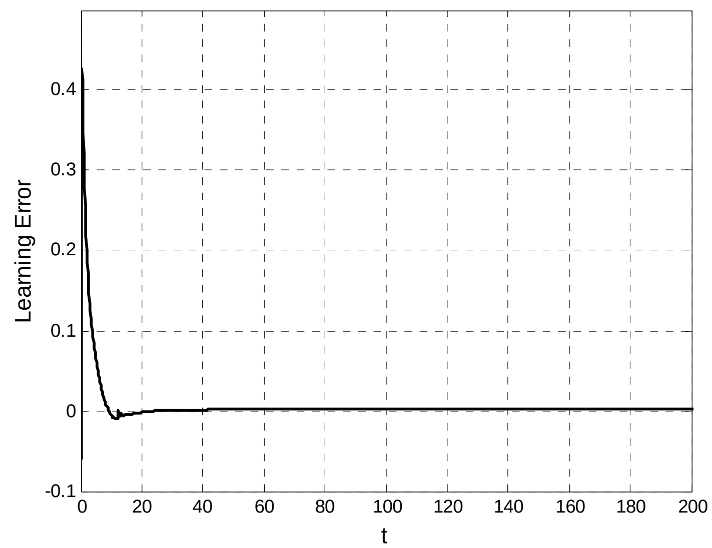

Fig. 4**.** Learning error of the RBF neural network

V. Conclusion

A neural network based model reference adaptive controller for ship steering system has been presented, in which a RBF neural network is utilized to adaptively compensate the nonlinearities in the plant. For the error between the output of the nonlinear function $d(\cdot)$ and the output of the RBF neural network is not available, the error between the reference model output and the plant output is used instead as the activation signal of the parameter adjusting law. Based on the Lyapunov stability theory, the updating law for the RBF neural network and practical stability are analyzed, which takes into account the neural network learning error. Numerical simulation was carried out to show the practical feasibility and performance of the proposed neural network-based adaptive control algorithm.

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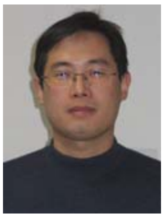

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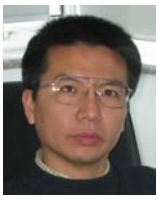

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