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Robust adaptive nonlinear observer design via multi-time scales neural network

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ABSTRACT

This paper deals with the robust adaptive observer design for nonlinear dynamic systems that have an underlying multiple time-scales structure via different time-scales neural network. The Lyapunov function method is used to develop a novel stable updating law for the multi-time scales neural networks model and prove that the state error, output estimation error and the neural network weights errors are all uniformly ultimately bounded around the zero point during the entire learning process. Furthermore, passivity-based approach is used to derive the robust property of the proposed multi-time scales neural networks observer. Compared with the other nonlinear observers without considering the time scales, the proposed observer demonstrates faster convergence and more accurate properties. Two examples are presented confirming the validity of the above approach.

1. Introduction

In many practical systems, only the input and output of a system are measurable. Therefore, estimating the states of a system plays a crucial role in modeling, monitoring or controlling the system. Linearization or quasi-linearization observer design methods limits the estimation accuracy for the practical nonlinear systems. Hence, different types of nonlinear observers have been developed during the past decade, i.e. the extended Luenberger observers [1], extended Kalman filter [2,3], sliding mode observer [4–7], and robust observer [32]. A comprehensive survey of the nonlinear observer is given in [8]. However, most of this work relies on exact a priori knowledge of the system nonlinearities.

The adaptive learning ability neural networks (NN) makes them powerful tools for identification [15,17,54], observation [9-20,31,37–39,42], monitoring [53] and control [47–49] of nonlinear system without any a priori knowledge about the system dynamics. Recent research [50,51] also shows that reinforcement learning may overcome the need for an exact model and achieve the optimality at the same time. The previous NN observer design can be roughly classified into three categories according to the NN structure, i.e. radial basis function (RBF) based observer, high order neural networks (HONN) based observer and dynamic neural networks (DNN) based observer. Linear-in-parameter RBF neural network was proposed to estimate the states of an affine SISO nonlinear system [9] and non-affine nonlinear systems [10] with the strong strictly positive real (SPR) condition imposed on the output error equation. In [11,12], a linear-in-parameter RBF based observer with the open-loop structure was proposed for the MIMO system, where the SPR assumption was relaxed. Furthermore, RBF based observers without strictly positive real (SPR) or any other strong assumptions were proposed in [13,14,37,42]. However, the static approximation of the gradient has been used to solve the dynamic back propagation problem like [13,37], which is just an approximate treatment and easy to fall into local optimum. Moreover, the main drawback of the RBF neural networks is that the weights' updating do not utilize any information on the local data structure and the function approximation is sensitive to the training data [55]. So far, there exist mainly two ways to improve the approximation ability of the NN-based observer design, i.e. high-order neural network (HONN) based observer and DNN based observer. For instance, the model free HONN based observer was proposed in [38,39] and time delay was considered in [31]. However, the HONN has the curse of dimensionality problem with the increase of order. The DNN approach, incorporating the feedback, provides an effective instrument to solve a wide spectrum of control problems such as identification, state estimation and trajectories tracking [15]. In [16], a new DNN observer based on practical stability theory was proposed to demonstrate the stability of weights trajectories. In [52], new delay-dependent stability criteria for DNN with time-varying delay are derived by dividing the delay interval into some variable subintervals employing weighting delays.

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In [17], a new learning procedure with a relay term to accelerate and improve the corresponding learning process. However, off-line training based on mean least square (MLS) method was required to select the nominal parameters in [16,17]. In [19], passivity theory is used to design the DNN observer and controller of partially known SISO nonlinear systems. A robust asymptotic DNN observer with time delay was proposed in [20]. Among these DNN observers design, the updating laws are too complicate and a linear approximation was also used via taylor series expansion to facilitate the stability analysis, which prevent such observers to real-world application.

All of the aforementioned neural networks observers do not consider the time-scales separation. Many practical nonlinear physical systems naturally possess the time-scale separation phenomena. Such as the car suspension system can be considered as a two-time-scale nonlinear dynamic system which have relations to road holding and ride quality respectively [30,35]. The plant perturbations originate from variations of physical parameters or arise because of a deliberate reduction in the complexity of a higher order mathematical model of the plant make it difficult to obtain the accurate mathematical model of this kind of nonlinear systems, which renders the observer design more difficult. Singularly perturbed methods can be used to obtain an approximate estimation of this nonlinear system via reduced-order observer design [33,34,36]. However, a basic requirement of perturbation methods is that the nonlinear system is completely known. This inspires the issue of model free observer design for nonlinear dynamic systems that have an underlying multiple time-scales structure. Recent results show that neural network with different time-scales are very effective for modeling the complex nonlinear system when we have incomplete model information [21,22].The passivity-based approach was used to derive stability conditions for dynamic neural networks with different time-scales in [23] and to prove that a gradient descent algorithm for weight adjustment was stable and robust to any bounded uncertainties in [24]. In our previous work [25], the indirect adaptive control for the nonlinear systems via multiple time scales neural networks has been established. However, it relies on the availability of all the systems states. This may be a rather stringent requirement for practical applications.

To the best of our knowledge, the design of nonlinear observer for model free nonlinear system including fast and slow phenomenon via multi-time scales neural networks has not been tackled within the control community. The main contributions of this paper are listed in the following. (1) It is the first time to investigate the nonlinear observer design via different time scales neural network, which has faster convergence speed compared with the common neural network observer; (2) By defining a Lyapunov function candidate based on quadratic functions of the weights and the estimation errors, a novel on-line updating law is introduced which can guarantee uniformly ultimately boundedness of the estimation error and weights error during the learning process. The proposed updating law can guarantee convergence without having the usual problems, such as local minima of the gradient [13,37], solving any LMI equation [52], Taylor's formula approximation [15] [43] and choosing the center vectors and width vectors of 'Gaussian' functions [14,44–46]. Moreover, the new learning law is designed in multi-time scales learning process rather than the traditional unique time scale and it can ensure fast learning convergence and closed-loop stability. (3) Mathematical proof of passivity for error dynamic system (map from approximation error and tuning parameters to state estimation) and neural network tuning system (map from tuning parameters norm and approximation error to state estimation) clearly indicates passivity of the robust property of the proposed multi-time scales neural networks observer. It is concluded that only the boundedness of input and output signals assure state bounded without any observability requirement, which makes the proposed technique free from observability requirement. This fact makes the proposed observer suitable for many complex applications where other design procedures might be restricted. The simulation results of two examples demonstrate faster convergence and more accurate properties of the proposed observer compared with the other observers without considering the time scales property.

The paper is organized as follows. In Section 2, some preliminary definitions are given. The proposed multi-time scales neural network observer is introduced in Section 3. Section 4 analyzes the robustness of the proposed observer based on the passivity approach. The simulation results of two examples are presented in Section 5 and the conclusion of this paper is presented in Section 6.

2. Preliminaries

2.1. Norm and trace property

The norm of a vector $x \in R^n$ and the L_2 norm of a matrix $A \in R^{m\times n}$ are denoted as

$\|x\| = \sqrt{x^T x} \qquad \|A\|_2 = \sqrt{\lambda_{\max}[A^T A]}$

where $\lambda_{\max}[\cdot]$ denotes the largest eigenvalue of the positive definite or positive-semidefinite matrix. We denote the smallest eigenvalue of a positive definite matrix $[\cdot]$ by $\lambda_{\min}[\cdot]$. Given $A = [a_{ij}]$ and $B \in R^{m\times n}$, the frobenius norm is defined by

$\|A\|_F^2 = tr(A^T A) = \sum a_{ij}^2$

where $tr(\cdot)$ denotes the trace of $(\cdot)$. The associated inner product is

$\langle A, B\rangle_F = tr(A^T B)$

The following properties of trace will be used to develop the updating law in this paper

1) $tr(AB) = tr(BA)$
2) $tr(A+B) = tr(A)+tr(B)$ for any $A, B \in R^{n\times n}$
3) $tr(yx^T) = x^T y$ for any $x, y \in R^{n\times 1}$

The L_∞ norm is defined as $\|x\|_\infty = \sup_{t\ge 0}|x(t)|$ and we say that $x \in L_\infty$ when $\|x\|_\infty$ exists.

2.2. Stability and passive systems

Definition 1. [28] Consider the nonlinear system $\dot{x} = f(x,u,t), y = h(x,t)$ with $x(t) \in R^n$. The solution is called uniformly ultimately bounded (UUB) if there exists a compact set $\Omega \in R^n$ such that for all $x(t_0) = x_0 \in \Omega$, there exist $\delta > 0$ and $t_0 > 0$ such that $\|x\| < \delta$, $\forall t \ge t_0$.

Definition 2. [26] Consider a class of nonlinear systems described by $\dot{x} = f(x,u,t), y = h(x,t)$ with the state $x(t) \in R^n$, input $u(t) \in R^m$, output $y(t) \in R^m$, $f: \in R^n \times R^m \to R^n$, $h: \in R^n \times R^m \to R^m$, then a system is said to be passive if the following inequality holds

$\dot{L}(t) \le y^T u - g(t)$

where the nonnegative function $L(t): R^n \to R$ is called storage function, $g(t)$ is positive semi-definite function of the state. One can further get the following inequality

$\int_0^T y^T(\tau)u(\tau)d\tau \ge \int_0^T g(\tau)d\tau - \gamma^2$

for all $T \ge 0$ and some $\gamma \ge 0$.

A system is dissipative if it is passive and in addition

$$\int_0^T y^T(\tau)u(\tau)d\tau \ne 0 \ \ implies \ \ \int_0^\infty g(\tau)d\tau > 0$$

State strict passivity (SSP) is defined as when a special sort of dissipativity occurs if $g(t)$ is a monic quadratic function of $\|x\|$ with bounded coefficients, where $x(t)$ is the internal state of the system. Then the L_2 norm of the state is bounded in terms of the L_2 inner product of output and input (i.e. the power delivered to the system), which can be used to conclude some internal bounded properties of the system without the usual assumptions of observability.