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Nonlinear Observer Applying Neural Network for A class of Chaotic System in the Presence of Uncertainty

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ABSTRACT

To control chaos phenomena with desirable performance, access to the states of plant is required. Due to complicated structure of chaotic systems, measurement of their states is a problem. In order to solve this problem, the observer must be added to control strategy for estimating the inaccessible states. In the present paper, the adaptive neural network observer is considered for chaotic system. This observer is tuned online and no exact information of nonlinear term is needed. This characteristic covers considerable part of uncertainty of plant.

KEYWORDS: ADAPTIVE NEURAL NETWORK OBSERVER; CHAOS; DUFFING SYSTEM; GENESIO-TESI SYSTEM.

1. INTRODUCTION

Chaos phenomenon is one of the most popular case studies in nonlinear and control science. The behaviours of chaotic states show sensitivity to initial conditions and its unpredictable trajectory come from the internal characteristic [1]. Because of undesirable effect of chaos, controlling of this phenomenon is an important purpose for scientists. In last two decades, different control methods have been presented, for instance, adaptive control [2-3] and robust control [4] can be mentioned.

According to the complicated structure of chaotic system, the uncertainties of these plants are considerable because of mismodelling and extreme nonlinearities. Also some of the states are inaccessible. Controlling under this constraint exhibits undesirable performance. To overcome this problem, the observer must be employed to estimate the states. Since the 1960's, many papers have been developed to overcome the problem of state estimation. Therefore,

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several nonlinear state estimation schemes have been presented to improve the accuracy of designing the control systems, such as extended Kalman filter and unscented Kalman filter. The literatures about these observers are extensive so that we refer the reader to [5-8]. A bunch of the observers that have been proposed is adaptive observer. The first nonlinear adaptive observer was presented in [9]. According to different circumstances, several observers were proposed in [10-12]. In this study, we use the adaptive neural network observer in which the neural network weights are tuned online [13]. The neural network can estimate any nonlinear system. The training process of neural network is implemented online and offline, but online weight adjusting is so useful and can be implemented in experimental projects. Online training has been used in nonlinear modelling, estimating and identification.

The rest of paper is organized as follows:

In next section the feature of this observer will be demonstrated. In section three, Duffing system will be introduced and the simulation of this plant with observer will be presented. In section four, this strategy will be implemented on the Genesio-Tesi system and in last section the conclusion of this paper will be rendered.

2. ADAPTIVE NEURAL NETWORK OBSERVER

In this section the structure of adaptive neural network will be demonstrated. This observer has been presented by Young H.kim et. al [13]. Consider single input-single output nonlinear plants with (A,C) in observer canonical form:

$$\begin{aligned} \dot{x} &= Ax + b[f(x) + g(x)u + d(t)] \\ y &= C^T x \end{aligned} \tag{1}$$

That $x \in R^n, y \in R, u \in R, b \in R^n$ and $d(t)$ is the unknown disturbance with known upper bound and $f, g : R^n \to R$ unknown smooth function.

The linear system is defined as an observer canonical form if A and C are given as follows:

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$$\dot{x} = Ax$$
$$y = C^T x$$

$$A = \begin{bmatrix} 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 1 & \dots & 0 \\ & & & & \\ 0 & 0 & \dots & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \qquad C = \begin{bmatrix} 1 \\ 0 \\ . \\ . \\ 0 \\ 0 \end{bmatrix} \tag{2}$$

The nonlinear observer state space equation is assumed as follows:

$$\dot{\hat{x}} = A\hat{x} + b[\hat{f}(\hat{x}) + \hat{g}(\hat{x})u - v(t)] + k[y - C^T \hat{x}]$$
$$\hat{y} = C^T x \tag{3}$$

There is not any limitation for vector b .

That $\hat{x}$ denotes the estimates of state x and $K = [k_1 k_2 .....k_n]^T$ is the observer gain chosen where $(A - KC^T)$ is strictly Hurwitz. $v(t)$ is robustifying term to control disturbance.

The neural network equation that used in this observer is as follows:

$$f(x) = W_f^T \sigma_f(x) + \varepsilon_f$$
$$g(x) = W_g^T \sigma_g(x) + \varepsilon_g \tag{4}$$

Where consist of two layers, the weight of first layer will be $V = I$ but the second layer weight must be tuned. One of the advantages of neural network that is used in this paper is that there is no need to data for training. In fact, in [13]; an equation is proposed for training the network using the equations correspondent to the stability of system and provides the value of network weight for system at each moment. Training of this neural network for two nonlinear terms is achieved from the following differential equation:

$$\dot{\hat{W}}_f = F_f \hat{\sigma}_f \tilde{y} - k_f F_f |\tilde{y}| \hat{W}_f$$
$$\dot{\hat{W}}_g = F_g \hat{\sigma}_g \tilde{y} u - k_g F_g |\tilde{y}| \hat{W}_g \tag{5}$$

Where σ denotes the activation function and $\tilde{y} = y - \hat{y}$ .Activation function is applied in the neural networks in different ways. In this observer the activation function for first layer is chosen sigmoid and for second layer is chosen purline.

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3. DUFFING SYSTEM

In this section, the proposed strategy will be implemented on the Duffing system. The state space equation of Duffing systems is as follows [14]:

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= -0.1x_2 - x_1^3 + 12\cos t + d(t) \\ y &= x_1 \end{aligned} \tag{6}$$

With the following initial condition:

$$x(0) = [2 \quad 2] \tag{7}$$

In the presented equation, $d(t)$ denotes the external disturbance. The trajectory of the states without input is as follows:

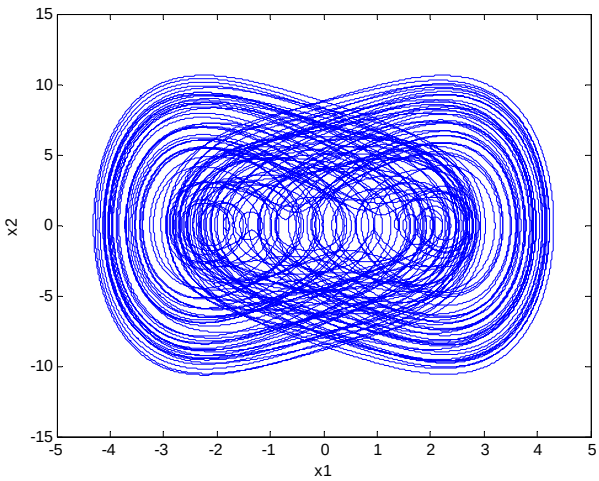

Figure 1: Duffing System

Now, it is assumed that the nonlinear term of the plant is unknown and we want to estimate the states with neural network observer in presence of external disturbance. The results of estimation are as follows:

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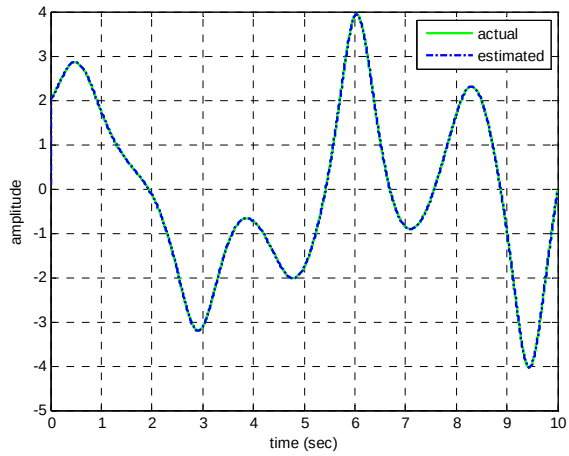

Figure 2: trajectory of state $x_1, \hat{x}_1$

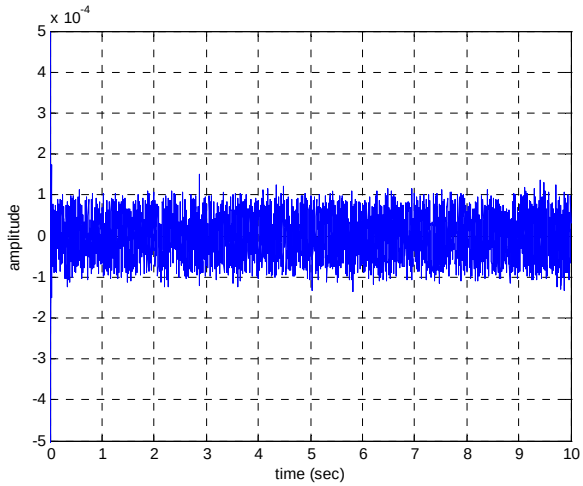

Figure 3: Estimation error of x_1

As shown above, the estimation error of x_1 is acceptable and the trajectory of actual and estimated state in fig.2 endorse it.

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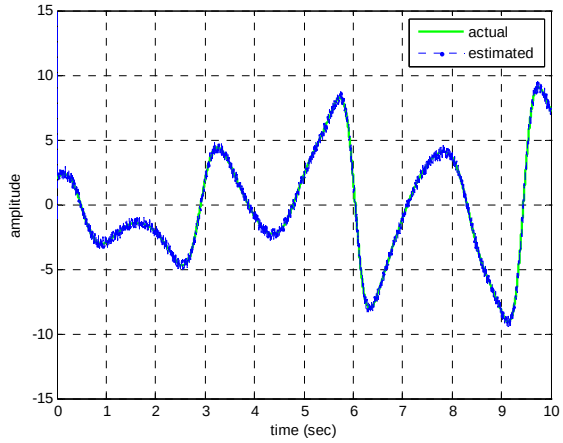

Figure 4: trajectory of state $x_2, \hat{x}_2$

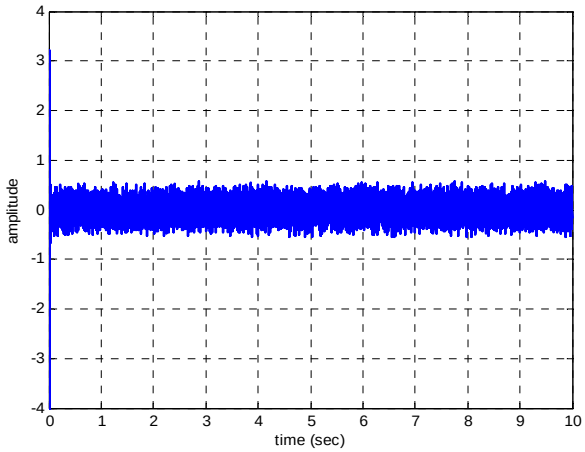

Figure 5: Estimation error of x_2

the estimation error of x_2 is desirable and the trajectory of actual and estimated state in fig.4 approves it. The parameters of observer are tuned as follows:

$$F_f = F_g = 5\times10^2 \ , \ k_f = k_g = 0.001 \ , \ k = [800 \quad 1000]$$

And the number of sigmoid function was applied for hidden layer is 15.

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4. GENESIO-TESI SYSTEM

This section demonstrates the application of proposed method on the Genesio-Tesi systems. State space equations of this type of systems are as follows [15]:

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= x_3 \\ \dot{x}_3 &= -6x_1 - 2.92x_2 - 1.2x_3 + x_1^2 + d \end{aligned} \tag{8}$$

With this initial condition:

$$x(0) = [0.5 \quad -1 \quad 0.5] \tag{9}$$

In presented equation $d(t)$ denotes external disturbance. The trajectory of the states without input is as follows:

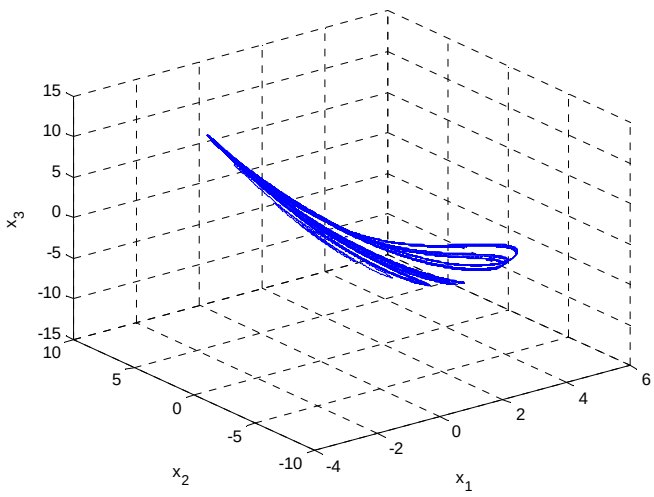

Figure 6: Genesio-Tesi system

Now, it is assumed that the nonlinear term of the plant is unknown and we want to estimate the states with neural network observer in presence of external disturbance. The result of estimation is as follows:

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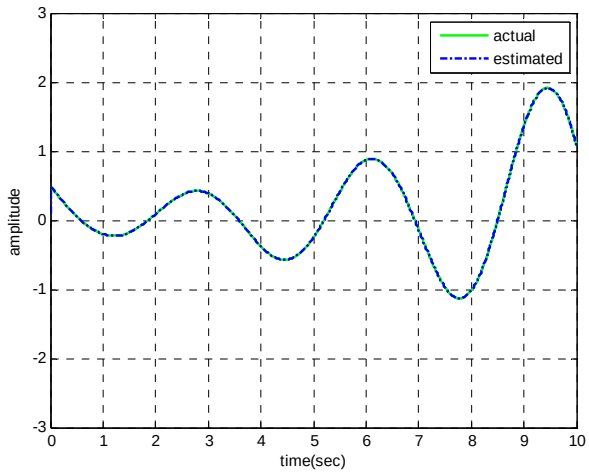

Figure 7: Trajectory of state $x_1, \hat{x}_1$

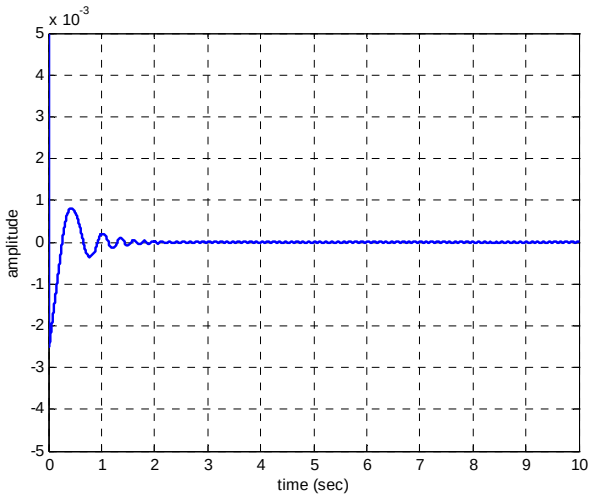

Figure 8: Estimation error of x_1

As shown above, the estimation error of x_1 is converged to zero and the trajectory of actual and estimated state in fig.7 approves it.

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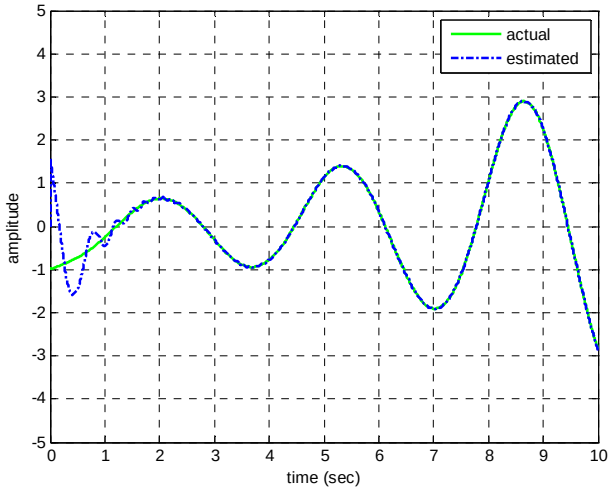

Figure 9: trajectory of state $x_2, \hat{x}_2$

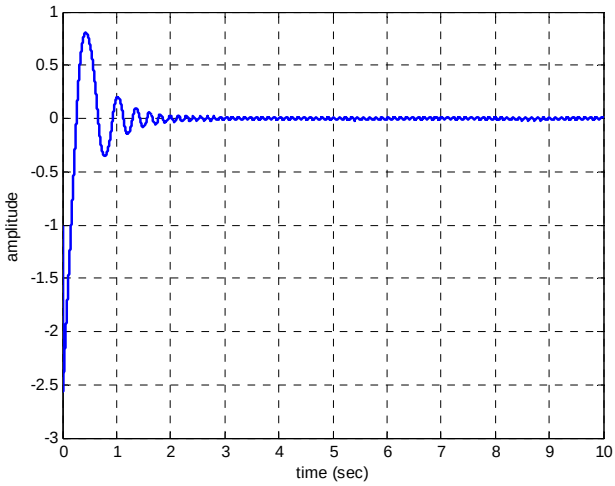

Figure 10: Estimation error of x_2

The estimation error of x_2 is converged to zero and the trajectory of actual and estimated state in fig.9 exhibit the capability of this observer.

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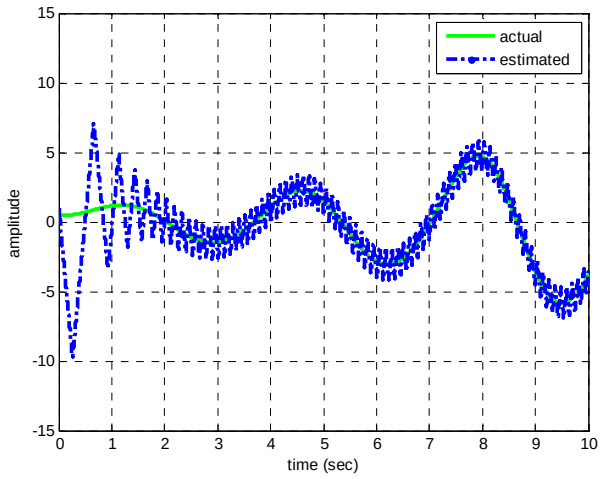

Figure 11: trajectory of state $x_3, \hat{x}_3$

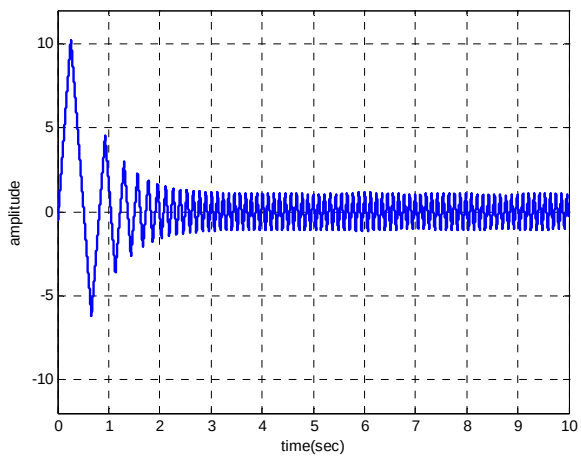

Figure 12: Estimation error of x_3

In fig.12, the trajectory of actual and estimated state confirmed the convergence of this estimation. The parameters of observer are tuned as follows:

$F_f = F_g = 5\times10^2$, $k_f = k_g = 0.001$, $k = [1000 \quad 1200 \quad 2000]$

And the number of sigmoid function was applied for hidden layer is 15.

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CONCLUSIONS

In this study, a suitable adaptive neural network observer has been employed for chaotic systems. At first, this observer has been implemented for 2nd order chaotic system, Duffing , and then this method has been considered for Genesio-Tesi system as a 3rd order chaotic system. The acceptable error estimation of chaotic systems confirmed that this observer can be used for this kind of systems. The simulation results endorse the capability of this observer for chaotic systems.

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