An Adaptive Neural Network Control Scheme for Stabilizing Chaos to the Stable Fixed Point

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A neural network control scheme with a novel adaptive learning rate is proposed to stabilize the chaotic trajectory of the chaotic system to a stable fixed point. A new approach is proposed to determine the stability of the fixed points in which the eigenvalues of the Jacobian matrix of the chaotic system at different values of the chaoticity parameter are evaluated and a look-up table is created to find a suitable fixed point that has a negative Lyapunov exponent. During learning phase of the neural network, weight parameters are adjusted so that the chaotic trajectory converges to a stable fixed point and the maximum Lyapunov exponent of the controlled system becomes negative. The effectiveness of the proposed method is investigated through simulation studies on 2 dimensional Ikeda map, which is produced by a semiconductor laser system.

KEYWORDS: chaos control, adaptive control, neural network, stabilitiy, bifurcation.

Introduction

Today, the electronic systems built up from micro-electronic circuits can exhibit chaotic behavior under some circumstances. For example, a digital filter can produce chaos under a certain condition, and this may be useful in crypto systems [27]; or some chaotic systems can be used for secure communication applications [4]. However, if chaos is not controlled, it may result in system failure and malfunction.

Thus, controlling chaos via different control schemes has received great interest in recent years after it

was first introduced by Ott et al. [25]. In OGY–like methods [28, 17, 5, 7], a small perturbation is applied to some parameter of the system to keep the chaotic trajectory in the vicinity of the target periodic orbit, when the chaotic trajectory enters a small neighborhood of the corresponding fixed point. However, it is not always an easy task to find a suitable control parameter in the system and a priori knowledge of the unstable periodic orbits is required to apply the control algorithm. Furthermore, these methods are highly sensitive to noise [12].

Linear controllers have also been used for chaos control. A piecewise linear feedback control [6] or a state feedback control [13] have been realized to stabilize the chaotic Chua's circuit. These types of controllers have a simple structure and can be easily applied in engineering problems; however, they are able to control the system for specific operating conditions.

The control problem of chaotic systems with uncertainty and disturbance has been studied by researchers using different robust control techniques. In [1], a sliding mode controller has been designed to stabilize the unstable periodic orbits of two-dimensional Hénon map with external disturbances. Sliding mode controllers have also been used to regulate and synchronize the chaotic systems to their equilibrium state [15, 29, 16]. In [20], a fuzzy model based design has been developed for trajectory tracking control of chaotic systems. However, fuzzy models are generally intuitive and require well-tuned control parameters.

Backstepping is one of the most promising Lyapunov based adaptive robust control techniques, which has been used for stabilization and tracking control of continuous time [31, 23, 24] and discrete time [21] chaotic systems as well as of nonlinear chaotic systems with bounded uncertainties and external disturbances [2, 22]. Adaptive backstepping controllers have a good performance for stabilizing the uncertain dynamical systems but ignore the parameter estimation errors in updating rules. To overcome these drawbacks, a flexible modular design has been proposed in [30] so that the parameter identifier and the controller modules have been independently designed.

Recently, neural network (NN) based control algorithms have attracted great interest in control and synchronization of chaotic systems because of their ability to deal with uncertainty and noise. In [19], a NN based algorithm has been utilized to stabilize the chaotic motion in chaotic Hénon map to a desired target trajectory. In [32], the chaotic motions of the Hénon and Logistic maps have been converted to a regular periodic motion by using a back propagation NN algorithm. In [10], a similar algorithm has been developed to control the chaotic trajectory of the Ikeda system to the equilibrium point.

In the stability analysis of chaotic systems, the Lyapunov exponent is an important quantitative indicator of chaotic dynamics, which is used to measure the convergence or divergence of nearby trajectories [9]. In [11], universal learning networks have been used to generate and eliminate the chaotic phenomena by controlling the maximum Lyapunov exponent of the system. In [26], a time delayed feedback controller has been proposed to stabilize the unstable periodic orbits of chaotic system, where the maximum Lyapunov exponent becomes negative.

In this paper, a back propagation NN algorithm with a novel adaptive learning rate [8] has been proposed to stabilize the chaotic trajectory of the discrete chaotic Ikeda system to the stable fixed point. First, the chaotic behavior of the Ikeda system depending on the choice of the chaoticity parameter has been investigated through bifurcation and the Lyapunov exponent analysis. Then, stability of the fixed points has been examined and a stability region for the stable fixed points with negative Lyapunov exponents has been defined. Based on the stability region, a lookup table has been built to determine the target stable fixed point for a chosen chaoticity parameter. With the improved NN scheme, weight parameters are adjusted so that the chaotic trajectory of the controlled system converges to a target stable fixed point, where the maximum Lyapunov exponent is negative. Time series plots and the maximum Lyapunov exponent calculations show that the proposed control scheme has been successfully applied to the chaotic system for controlling the chaotic trajectory.
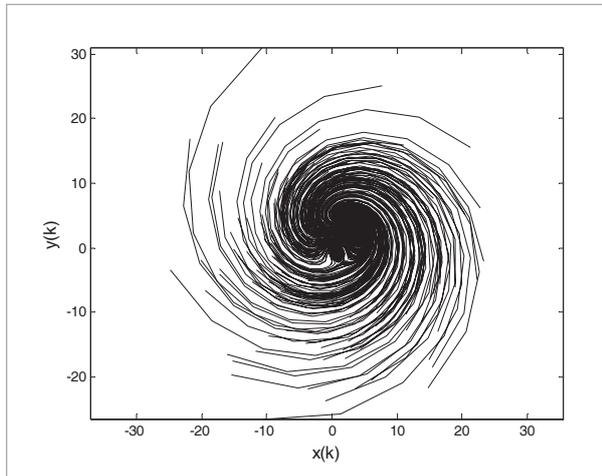
Discrete time chaotic system

In this paper, Ikeda map, which represents the dynamics of a laser pulse in an optical cavity, is studied as a two-dimensional chaotic system. The map equation is given in [14] as:

$$x(k+1) = F(x,y) = p + B(x(k)\cos(t) - y\sin(t)),$$
$$y(k+1) = G(x,y) = B(x(k)\cos(t) + y\sin(t)), \qquad (1)$$
$$t = k - \alpha/(1 + x_k^2 + y_k^2).$$

Eq. (1) exhibits a strange attractor with parameters $p = 1, \alpha = 6, k = 0.4$ and $B = 0.9$ as shown in Fig. 1 [3].

Figure 1

The attractor of Ikeda map

For a 2D map, (x^*, y^*) is a fixed point if it satisfies $F(x^*, y^*) = x^*, G(x^*, y^*) = y^*$. Let (x^*, y^*) be the fixed point, then, using Taylor expansions, one can obtain the Jacobian matrix as:

$$J(x,y) = \begin{bmatrix} \dfrac{\partial F}{\partial x} & \dfrac{\partial F}{\partial y} \\ \dfrac{\partial G}{\partial x} & \dfrac{\partial G}{\partial y} \end{bmatrix}_{x=x^*, y=y^*} \qquad (2)$$

To understand the stability of a fixed point, one can check the eigenvalues of the Jacobian matrix given by Eq. (2). If the magnitude of each eigenvalue is smaller than one, then the fixed point is attracting a stable point. If the magnitude of each eigenvalue is bigger than one, then the fixed point is repelling an unstable point. If at least one eigenvalue is smaller than one and at least one eigenvalue is bigger than one, then the fixed point is unstable saddle point.

In order to evaluate the chaotic behavior of a dyna-

mical system, Lyapunov exponents are used to identify the separation or attraction of initially nearby trajectories. Let M be the matrix given by the product of Jacobians as:

$$M = \prod_{i=1}^{N} J(x_i, y_i). \qquad (3)$$

Then, Lyapunov exponents of two-dimensional map, σ_1 and σ_2, are calculated by:

$$\sigma_1 = \lim_{N \to \infty} \frac{1}{N} In|\lambda_1|,$$
$$\sigma_2 = \lim_{N \to \infty} \frac{1}{N} In|\lambda_2|, \qquad (4)$$

where λ_1 and λ_2 are the eigenvalues of M. It is well known that the maximum Lyapunov exponent, $\sigma_{max} = \max\{\sigma_1, \sigma_2\}$, is used to characterize the chaotic behavior of the system. If $\sigma_{max} > 0$, the system behaves chaotically; otherwise, it is stable.

The chaotic behavior of the Ikeda map given by Eq. (1) changes with respect to the chaoticity parameter B. Fig. 2 and Fig. 3 show the variation of the maximum Lyapunov exponents and the bifurcation diagram of the Ikeda map for the parameter B in the range of $(0,1]$, respectively.

As can be seen from Fig. 2 and Fig. 3, for $B > 0.4$, the maximum Lyapunov exponent is positive and period

Figure 2

The variation of maximum Lyapunov exponent with respect to the chaoticity parameter
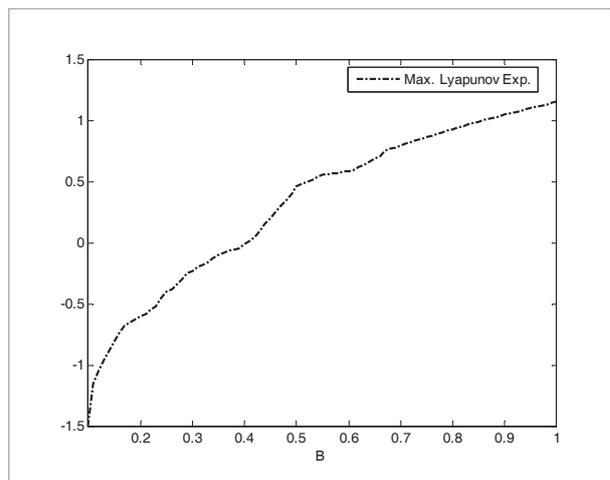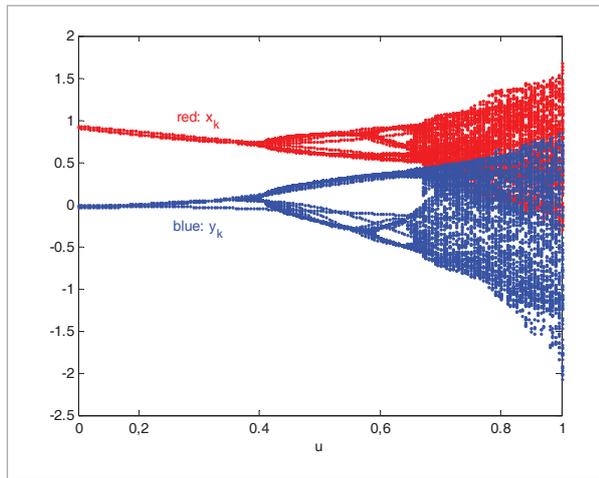
Figure 3

Bifurcation diagram

doubling occurs, which leads to chaotic behavior. In order to understand the stability of the fixed points, the magnitude of the eigenvalues of the Jacobian matrix given by Eq. (2) has been investigated. Fig. 4 shows the variation of the maximum eigenvalues, which correspond to the fixed points, with respect to the chaoticity parameter B.

Figure 4

The dependence of the fixed points on the chaoticity parameter
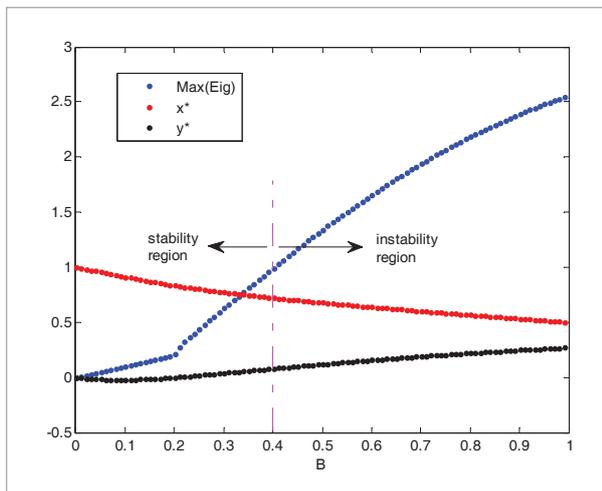
It is clear that, for $B > 0.4$, the magnitude of the maximum eigenvalues is bigger than one. Therefore, the

pairs of fixed points, (x^*, y^*), corresponding to the B values greater than "0.4" fall into the instability region, which means that all fixed points for $B > 0.4$ are unstable. On the other hand, for $0 < B < 0.4$, all fixed points fall into the stability region.

From Fig. 4, it is seen that x^* is monotonically decreasing in the interval (0.5, 0.91) and y^* is monotonically increasing in the interval (–0.02, 0.27) with respect to B. Thus, in order to determine the target stable fixed point according to the chaoticity parameter B in the stability region, the following linear interpolations can be utilized as:

$$
\begin{aligned}
x^* &= \operatorname{interp}(\overline{\mathrm{B}}, \overline{\mathrm{x}}, \mathrm{B_s}), \\
y^* &= \operatorname{interp}(\overline{\mathrm{B}}, \overline{y}, \mathrm{B_s}),
\end{aligned}
\tag{5}
$$

where interp is interpolation function, $\overline{x}$, $\overline{y}$ are the fixed point vectors and $\overline{\mathrm{B}}$ is the chaoticity parameter vector in the range of $(0,1)$. $\mathrm{B_s}$ can be chosen freely in the stability region, i.e. $(0, 0.4)$. Considering together with Fig. 2, the maximum Lyapunov exponent of any fixed point in the stability region, as shown in Fig. 4, is negative. So, in this study, the aim is to keep the chaotic trajectory of the Ikeda system in the vicinity of the target stable fixed point that can be determined by Eq. (5).

Alternative control scheme

Although there have been many studies in the literature on the stabilization of the chaotic systems, it is still a difficult task to determine a suitable fixed point where all the Lyapunov exponents are negative. Among these studies, a time-delayed feedback controller developed in [26] is the most effective one. In it, the chaotic system is perturbed by small changes in control parameters in such a way that the largest Lyapunov exponent related to an unstable periodic orbit (UPO) becomes negative as shown in Fig. 5, so the UPO becomes stable and the chaotic trajectory converges to this stable fixed point.

As can be seen from Fig. 5, the largest Lyapunov exponent evaluated for different values of the control parameters, R and K, is negative. Thus, stabilization can be achieved for all values of R. Although this

method is very useful and simple for transforming the unstable fixed points to stable ones, it is not always possible to find an appropriate control parameter or the system can go unstable if the perturbation time is long.

Figure 5

The largest Lyapunov exponent for different control parameters
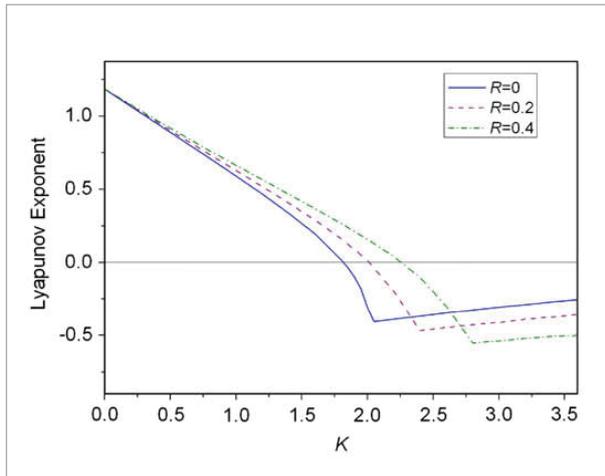
In this paper, in order to eliminate these drawbacks of the existing control methods, the eigenvalues of the Jacobian matrix of the chaotic system have been evaluated for different values of the chaoticity parameter, which leads to chaotic behaviour. The fixed points are stable for the chaoticity parameter that makes the maximum eigenvalue of the system smaller than "1". Based on the value of the maximum eigenvalues, a set of suitable fixed points has been created and the suitable one is determined by using a lookup table. Then, an adaptive neural network control scheme has been applied to chaotic system to force the chaotic trajectory to converge to the stable fixed point. Hence, the proposed method is not sensitive to variation in chaotic dynamics.

Proposed control scheme

The proposed control scheme is a back propagation neural network with a novel adaptive learning rate consisting of three layers of neurons (input layer, hidden layer and output layer), as shown in Fig. 6 [18].

Figure 6

The proposed neural network topological structure
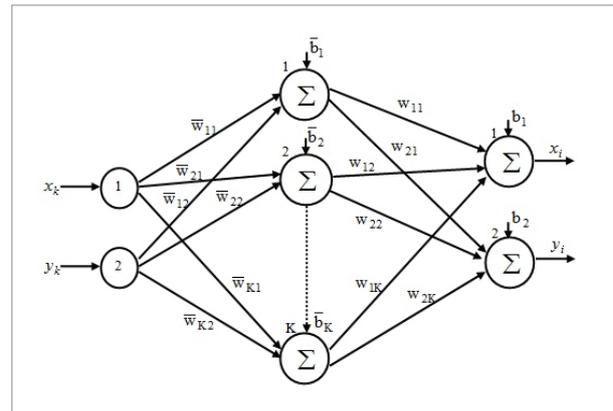
Here, $(x_k, y_k), k = 1,2,.....N$, are the input patterns generated iteratively from Eq. (1); N is the finite number of input patterns; (x_i, y_i) are the output patterns that should have to be approximated to the fixed points, (x^*, y^*). The generalized model of the proposed control system is shown in Fig. 7.

Figure 7

The model of the proposed control scheme
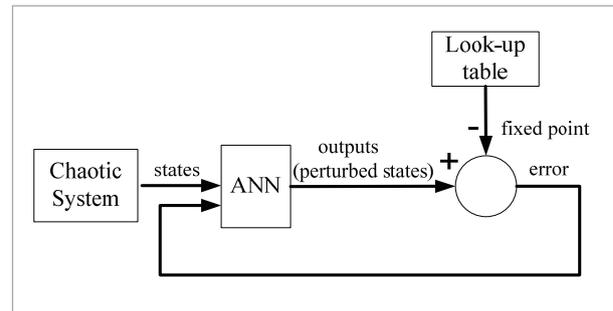
In the adaptive neural network (ANN) block in Fig. 7, the error is back-propagated to update the weights, and the outputs (perturbed states) are converged to the stable fixed point. The learning phase of the ANN has two steps. In the first step, the output of the network is calculated based on the structure of the network using previous weights and bias values from the first layer to the forward. The following calculations are done in the first step.

The input to the k th neuron of the hidden layer is denoted by I_K and is given by:

$$I_K = x_k \overline{w}_{K1} + y_k \overline{w}_{K2} + \overline{b}_K \qquad (6)$$

where

$\overline{w}_{K1}$ and $\overline{w}_{K2}$ are the weights between the k th neuron of the hidden layer. $\overline{b}_K$ is the bias value of the k th neuron in the hidden layer. By applying the tangent sigmoid activation function F on I_K, the output $\overline{O}_{pK}$ is obtained as:

$$F(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \qquad (7)$$

$$\overline{O}_{pK} = F(I_K). \qquad (8)$$

The network outputs are given by:

$$x_i = F\left(\sum_{k=1}^{K} \overline{O}_{pK} w_{1K} + b_1 \right), \qquad (9)$$

$$y_i = F\left(\sum_{k=1}^{K} \overline{O}_{pK} w_{2K} + b_2 \right). \qquad (10)$$

In the second step, the weights and bias values are updated adaptively based on the error values, $E_{x_i} = x^* - x_i$, $E_{y_i} = y^* - y_i$, from the last layer to the back. The adaptation rules for the weight and bias values between the output and hidden layers are calculated by the following equations:

$$\begin{aligned} w_{1Knew} &= w_{1Kold} + \Delta w_{1K}(k+1), \ k = 1,2...N, \\ w_{2Knew} &= w_{2Kold} + \Delta w_{2K}(k+1), \ k = 1,2...N. \end{aligned} \qquad (11)$$

$$\begin{aligned} b_{1new} &= b_{1old} + \Delta b_1(k+1), \\ b_{2new} &= b_{2old} + \Delta b_2(k+1). \end{aligned} \qquad (12)$$

In Eqs. (11), (12), second terms are calculated as:

$$\begin{aligned} \Delta w_{1K}(k+1) &= \eta_x \delta_{1K} \overline{O}_{pK}, \\ \Delta w_{2K}(k+1) &= \eta_y \delta_{2K} \overline{O}_{pK}, \end{aligned} \qquad (13)$$

$$\begin{aligned} \Delta b_1(k+1) &= \eta_x \delta_{1K}, \\ \Delta b_2(k+1) &= \eta_y \delta_{2K}, \end{aligned} \qquad (14)$$

$$\begin{aligned} \delta_{1K} &= E_{x_i} x_i (1 - x_i), \\ \delta_{2K} &= E_{y_i} y_i (1 - y_i), \end{aligned} \qquad (15)$$

where η_x and η_y are the adaptive learning rates which are varied according to the error functions and updated as:

$$\eta_{x,y} = \begin{cases} \eta_{x,y} \phi, \ \phi > 1, \left| E_{x_{i+1},y_{i+1}} \right| \leq \left| E_{x_i,y_i} \right| \\ \eta_{x,y} \varsigma, \ \varsigma < 1, \left| E_{x_{i+1},y_{i+1}} \right| > \left| E_{x_i,y_i} \right| \\ \eta_{x,y} \qquad , \left| E_{x_i,y_i} \right| \leq E_t, \forall i \in N \end{cases} \qquad (16)$$

This rule is applied until a desired error response, E_t, is achieved. In a similar way, the adaptation rules for the weight and bias values between the hidden and input layers are calculated by the following equations:

$$\begin{aligned} \overline{w}_{K1new} &= \overline{w}_{K1old} + \Delta \overline{w}_{K1}(k+1), \ k = 1,2...N, \\ \overline{w}_{K2new} &= \overline{w}_{K2old} + \Delta \overline{w}_{K2}(k+1), \ k = 1,2...N, \end{aligned} \qquad (17)$$

$$\overline{b}_{Knew} = \overline{b}_{Kold} + \Delta \overline{b}_K(k+1), k = 1,2.....N. \qquad (18)$$

In Eqs. (17), (18), second terms are calculated as:

$$\Delta \overline{w}_{K1}(k+1) = \eta_z \overline{\delta}_{K1} x_i, \qquad (19)$$

$$\Delta \overline{w}_{K2}(k+1) = \eta_z \delta_{K1} y_i, \qquad (20)$$

$$\Delta \overline{b}_K(k+1) = \eta_z \overline{\delta}_{K1}, \qquad (21)$$

$$\begin{aligned} \overline{\delta}_{K1} &= (\delta_{1K} w_{1Kold} + \delta_{2K} w_{2Kold}) c(k), \\ c(k) &= \overline{O}_{pK}(1 - \overline{O}_{pK}), \end{aligned} \qquad (22)$$

where η_z is also changed adaptively as:

$$\eta_z = \begin{cases} \eta_z \phi, \ \left| E_{x_{i+1}} \right| + \left| E_{y_{i+1}} \right| \leq \left| E_{x_i} \right| + \left| E_{y_i} \right| \\ \eta_z \varsigma, \ \left| E_{x_{i+1}} \right| + \left| E_{y_{i+1}} \right| > \left| E_{x_i} \right| + \left| E_{y_i} \right| \\ \eta_z, \ \left| E_{x_i} \right| + \left| E_{y_i} \right| \leq E_t \ \text{for} \ \forall i \in N \end{cases} \qquad (23)$$

where $\phi > 1$ and $\varsigma < 1$ are appropriate constants. With above updating rules, the output of the network converges to the target stable fixed point.

Simulation results and discussion

In this section, numerical simulations are carried out on Ikeda system to show the effectiveness of the proposed

control method. The objective is to stabilize the chaotic trajectory of Ikeda map given by Eq. (1) to a stable target fixed point, which has been determined by Eq. (5).

In this study, B_s was chosen as 0.3 in the interval of $(0, 0.4)$, where the maximum Lyapunov exponent is negative. For $B_s = 0.3$, the stable fixed point has been calculated as $x^* = 0.772$, $y^* = 0.038$. For this target point, the proposed neural network has been trained using a set of some arbitrary trajectories with random initial values, and a training set with 500 input patterns has been constructed for test purpose.

The ANN training parameters are given in Table 1. The optimal values of these parameters are obtained based on the simulation trials.
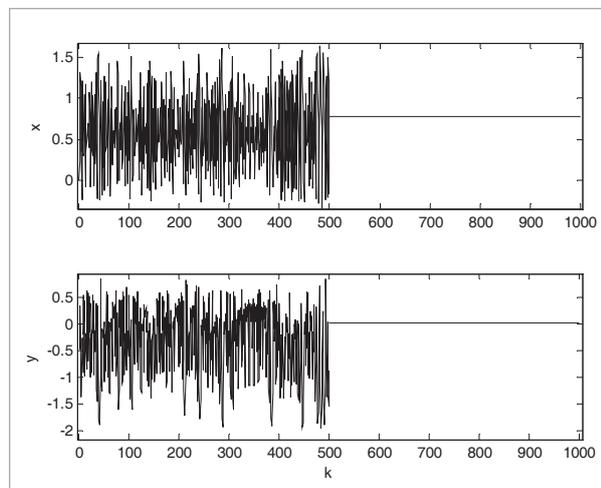
Table 1

ANN training parameters

Parameters	Values
Transfer function in hidden and output layers	tansig
Number of hidden neurons	10
Initial weights and bias	[0,0]
Learning rates, $\eta_x = \eta_y = \eta_z$	0.1
ϕ	2
ς	0.9

Fig. 8 shows the time series plot of the system states, when the proposed control scheme is applied.

Figure 8

Time series plot

As can be seen from Fig. 8, the state variables reach the stable target fixed point immediately after the control action has been switched on at $k = 500$.

Figure 9

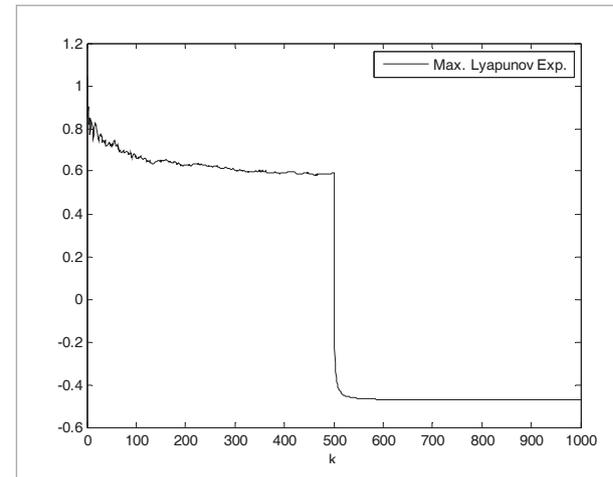Variation of maximum Lyapunov exponent of the controlled system (after $k = 500$)

Fig. 9 shows the variation of the maximum Lyapunov exponent, σ_{max}, of the chaotic system as well as the controlled system for this training set. It is clear that the positive Lyapunov exponent of the chaotic system becomes negative after control action has been taken.

Conclusions

In this paper, the control of chaos, which may occur in electronic systems, has been studied. For this purpose, a neural network control scheme with an adaptive learning rate has been proposed to control the chaotic trajectory of the Ikeda type chaotic system in the vicinity of the stable fixed point. The stability of the fixed points has been examined by calculating the eigenvalues of the Jacobian matrix at different values of the chaoticity parameter in a certain range that affects the chaotic properties of the system. The variation of the maximum Lyapunov exponent with respect to the chaoticity parameter has been investigated, and a relationship between the maximum Lyapunov exponent and the stability of the fixed points has been presented. Simulation studies showed that the proposed method can successfully stabilize the chaotic trajectory of the system to the target stable fixed point, where the maximum Lyapunov exponent is negative.

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Summary / Santrauka

A neural network control scheme with a novel adaptive learning rate is proposed to stabilize the chaotic trajectory of the chaotic system to a stable fixed point. A new approach is proposed to determine the stability of the fixed points in which the eigenvalues of the Jacobian matrix of the chaotic system at different values of the chaoticity parameter are evaluated and a look-up table is created to find a suitable fixed point that has a negative Lyapunov exponent. During learning phase of the neural network, weight parameters are adjusted so that the chaotic trajectory converges to a stable fixed point and the maximum Lyapunov exponent of the controlled system becomes negative. The effectiveness of the proposed method is investigated through simulation studies on 2 dimensional Ikeda map, which is produced by a semiconductor laser system.

Straipsnyje siūloma neuroninio tinklo valdymo schema, pasižyminti nauju adaptyviu mokymosi greičiu tam, kad būtų galima stabilizuoti chaotiškos sistemos chaotišką trajektoriją iki stabilaus ir pastovaus taško. Siūlomas naujas metodas, leidžiantis nustatyti pastovių taškų, kuriuose vertinamas chaotiškos sistemos Jakobiano matricos tikrinių verčių stabilumas skirtinguose chaotiškumo parametrų įverčiuose. Sudaryta lentelė, kurioje galima rasti tinkamą pastovų tašką, turintį neigiamą Liapunovo rodiklį. Neuroninio tinklo mokymosi fazės metu svorio parametrai sureguliuojami taip, kad chaotiška trajektorija konverguoja į stabilų pastovų tašką, maksimalus valdomos sistemos Liapunovo rodiklis tampa neigiamas. Siūlomo metodo efektyvumas tiriamas per simuliacinius 2D Ikedos žemėlapio, sukurto puslaidininkio lazerio sistema, tyrimus.