H_∞ StateestimationStochasticneutraltypeneuralnetworkswithtimevaryingdelaysandMarkovianJumpingParameters

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1. INTRODUCTION & OBJECTIVE

The delay-dependent designof H_∞ State estimation Stochastic neutral type neural networks withtime varying delays and Markovian Jumping Parameters is considered in this paper.By constructing a suitableLyapunov-Krasovskii functional, a delay-dependent condition is established to guarantee the estimation errorsystems to be asymptotical mean-square stable and achieve a prescribed H_∞ performance index.Both delay-dependent and delay-independent sufficient conditions for the existence of desired state estimators are derivedin terms of linear matrix inequalities (LMIs) to guarantee the Markov jump delayed neural frameworks to bepassive.PassivityandPassificationproblemsaretackledbyusingmode-dependent. Finally, a numerical example demonstrate that the proposed approaches are effective

2. RESULTS & HIGHLIGHTS OF IMPORTANT POINTS

The problem of H_∞ performance state estimation for stochastic neutral type neural networks with timevarying delays and Markovian jumping parameters has been investigated in this paper.Delay-dependent anddelay-independent design criteria have been established. Our future research topics would include the followingissues:

(1). To remove the restriction of the derivative of delay $\mu < 1$;

(2). The H_∞ state estimation for stochastic neural networks with Markovian jump parameters or mixed time-varying delays, discrete-time stochastic neural networks, stochastic genetic regulatory networks and neutralstochasticneuralnetworks;

(3). Thegeneralized H_∞ stateestimationproblemforstochasticneuralnetworks.

Numerical Example

In this section, an example is given to demonstrate the effectiveness of the proposed method.Consider athree-neuronstochasticneuralnetwork(1)-(3)withparameters:

$$A_1=\begin{bmatrix}2 & 0\\ 0 & 3\end{bmatrix},\ W_{01}=\begin{bmatrix}-0.4 & -0.2\\ 0.3 & -0.2\end{bmatrix},\ W_{11}=\begin{bmatrix}-0.2 & -0.1\\ 0.1 & 0.2\end{bmatrix},\ W_{21}=\begin{bmatrix}-0.2 & -0.9\\ -0.9 & 0.25\end{bmatrix},$$

$$B_{11}=\begin{bmatrix}0.3 & -0.2\\ -0.2 & 0.5\end{bmatrix},\ B_{21}=\begin{bmatrix}-0.4 & 0.3\\ 0.2 & 0.4\end{bmatrix},\ H_{11}=\begin{bmatrix}0.2 & 0.2\\ 0.2 & 0.8\end{bmatrix},\ C_1=\begin{bmatrix}-0.2 & 0.1\\ 0.8 & 0.7\end{bmatrix},$$

$$H_{21}=\begin{bmatrix}0.2 & -0.6\\ -0.6 & 0.6\end{bmatrix}, D_1=\begin{bmatrix}-0.2 & 0.3\\ 0.4 & 0.1\end{bmatrix},\ L=\begin{bmatrix}0.3 & 0.4\\ 0.5 & 0.8\end{bmatrix},\ \Sigma_1=0, \Sigma_2=\begin{bmatrix}1 & 0\\ 0 & 1\end{bmatrix},$$

$$F_1=0, F_2=\begin{bmatrix}-0.5 & 0\\ 0 & -0.5\end{bmatrix},\ I\begin{bmatrix}1 & 0\\ 0 & 1\end{bmatrix}.$$

UsingMatlabLMIToolboxtosolvetheLMIinTheorem2,weobtainthesolutionsasfollows:

$$P_1=\begin{bmatrix}0.2937 & 0.0702\\ 0.0702 & 0.2362\end{bmatrix}, Q=\begin{bmatrix}-2.9391 & -0.3554\\ -0.3554 & -3.4313\end{bmatrix},\ R=\begin{bmatrix}1.9398 & -0.3190\\ -0.3190 & 1.7739\end{bmatrix},$$

$$R_1=\begin{bmatrix}-2.0117 & -0.0125\\ -0.0125 & -2.0060\end{bmatrix},\ Z=\begin{bmatrix}-0.4324 & 0.1453\\ 0.1453 & -0.4212\end{bmatrix}, T_1=\begin{bmatrix}0.0203 & -0.1783\\ -0.1783 & -0.2678\end{bmatrix},$$

$$\lambda_1=1.1289, \lambda_2=1.1389.$$

ByTheorem3.2,when $\mu=1.6, \tau=0.925, \gamma=1.14570, h_d=1.2$,gainthematrixof(44)canbedesignedas:

$$K_1=\begin{bmatrix}0.2686 & -0.3618\\ -0.8347 & -1.0263\end{bmatrix}$$

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