Control and Intelligent Systems, Vol. 35, No. 4, 2007

COMPUTATION OF ROBUST H_∞ CONTROLLERS FOR TIME-DELAY SYSTEMS USING GENETIC ALGORITHMS

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Abstract

This paper presents an evolutionary computation approach to design robust H_∞ controllers for linear uncertain time-delay systems via a combination of genetic algorithms (GAs) and linear matrix inequalities (LMIs). Both state feedback and static output feedback controllers can be designed with this approach. It is demonstrated by numerical examples that the controllers designed by this approach can allow larger delay size than previous results for the same H_∞ performance bound. Hence, this approach is less conservative than existing methods.

Key Words

Genetic algorithms, linear matrix inequalities, state feedback, output feedback, time-delay systems

1. Introduction

Considerable research efforts have been devoted to the problem of delay-dependent robust H_∞ controller design for linear uncertain time-delay systems. The main objective of the delay-dependent H_∞ control is to obtain a controller such that the maximal delay size for a fixed H_∞ performance bound is allowed or the minimal H_∞ performance bound for a fixed delay size is achieved. Hence, the conservatism in the delay-dependent H_∞ control is measured by the allowable delay size or the minimal performance bound obtained. During the last decades, various approaches have been proposed to reduce the conservatism of delay-dependent conditions by using new bounding for cross terms or choosing new Lyapunov–Krasovskii functional [1–7]. In particular, a less conservative delay-dependent H_∞ control was proposed in [5] for linear systems with a state delay based on a new Lyapunov–Krasovskii functional. It was also shown that the proposed method is much less conservative than previously existing results presented in [1, 3] . Further improved conditions for the solvability of the delay-dependent H_∞ control are given in [7] where newly obtained results with reduced conservatism are established.

In most of the previously published research works, however, the H_∞ controller synthesis conditions are presented in terms of nonlinear matrix inequalities to reduce the conservatism. Although iterative algorithms have been developed to solve the nonlinear matrix inequalities due to the nonconvex feasibility problem, conservatism can be significant and the iterative algorithms can only locate suboptimal solutions. Moreover, these works are only focused state feedback control. At present, not a lot of efforts have been given to designing the static output feedback controllers for time-delay systems although the realization of the static output feedback controllers is more practical.

This paper develops an algorithm for designing both state feedback and static output feedback H_∞ controllers for the linear uncertain time-delay systems. To circumvent the nonlinear matrix inequality problems involved in the delay-dependent conditions, the genetic algorithm (GA), which has been extensively applied in many areas [8, 9] due to its high potentialities in global optimization, is employed to search for the possible solutions. Specifically, in each generation of the GA, potential controller candidates are created for the verification of the closed-loop H_∞ performance via its linear matrix inequality (LMI) characterization. Numerical examples show that the proposed approach can achieve a significant reduction in the conservatism when compared with previous results.

2. Problem Formulation

Consider the following state-delayed systems:

$$\begin{aligned}\dot{x}(t) &= [A + \Delta A(t)]x(t) + [A_1 + \Delta A_1(t)]x(t - \tau(t)) \\ &\quad + [B + \Delta B(t)]u(t) + B_w w(t)\end{aligned}$$

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Recommended by Prof. K. Krishnamurthy
(paper no. 201-1865)

$$z(t) = \begin{bmatrix} C_0 x(t) + D_w w(t) \\ C_1 x(t-\tau) \\ Du(t) \end{bmatrix}$$

$$\begin{aligned} y(t) &= Cx(t) \\ x(t) &= \phi(t), \quad t \in [-\overline{\tau}, 0] \end{aligned} \tag{1}$$

where $x(t) \in \mathbb{R}^n$ is the state; $u(t) \in \mathbb{R}^m$ is the control input; $w(t) \in \mathbb{R}^p$ is the disturbance input that belongs to $L_2[0,\infty)$; $y(t) \in \mathbb{R}^p$ is the measured output; $z(t) \in \mathbb{R}^l$ is the regulated output; $\tau(t)$ is the time-varying delay of the system state and is assumed to satisfy $0 < \tau(t) \leqslant \overline{\tau}$, $\dot{\tau}(t) \leqslant \mu$, where $\overline{\tau}$ and μ are given constant scalars; $\phi(t)$ is a continuous initial function; A, A_1, B, B_w, C_0, C_1, D, D_w, and C are known real constant matrices with appropriate dimensions; $\Delta A(t)$, $\Delta A_1(t)$, and $\Delta B(t)$ are time-varying uncertain matrices of the form:

$$[\Delta A(t) \quad \Delta A_1(t) \quad \Delta B(t)] = MF(t)[N \quad N_1 \quad N_b] \tag{2}$$

where M, N, N_1, and N_b are constant matrices, and $F(t) \in \mathbb{R}^{q\times k}$ is an unknown matrix satisfying $F(t)F(t)^T \leqslant I$. Such parameter uncertainties $\Delta A(t)$, $\Delta A_1(t)$, and $\Delta B(t)$ are said to be admissible. In this paper, we are interested in designing a memoryless controller $K \in \mathbb{R}^{m\times p}$ such that:

$$u(t) = Ky(t) = KCx(t) \tag{3}$$

such that, for any time delay $\tau(t)$ satisfying $0 < \tau(t) \leqslant \overline{\tau}$, $\dot{\tau}(t) \leqslant \mu$,

1. The closed-loop system is asymptotically stable for all admissible uncertainties.
2. The closed-loop system guarantees, under zero initial condition, $\|z\|_2 < \gamma\|w\|_2$, where $\gamma > 0$ is a prescribed constant, for any nonzero $w(t) \in L_2[0,\infty)$.

A controller K satisfying the above conditions is said to be a *γ-suboptimal H_∞ controller*.

Now, we provide the following theorem based on the recently published result in [7] with proof omitted.

Theorem 1. If there exist matrices $P > 0$, $Q > 0$, $Z > 0$, Y, W, K, and a scalar $\varepsilon > 0$ such that the following matrix inequality holds:

$$\begin{bmatrix} \Phi_1+\Gamma & \Phi_2+\Psi & \overline{\tau}Y & PB_w & \overline{\tau}A^TZ+\overline{\tau}(BKC)^TZ & C_0^T & 0 & (KC)^TD^T & PM \\ * & \Phi_3+\varepsilon N_1^TN_1 & \overline{\tau}W & 0 & \overline{\tau}A_1^TZ & 0 & C_1^T & 0 & 0 \\ * & * & -\overline{\tau}Z & 0 & 0 & 0 & 0 & 0 & 0 \\ * & * & * & -\gamma^2I & \overline{\tau}B_w^TZ & D_w^T & 0 & 0 & 0 \\ * & * & * & * & -\overline{\tau}Z & 0 & 0 & 0 & \overline{\tau}ZM \\ * & * & * & * & * & -I & 0 & 0 & 0 \\ * & * & * & * & * & * & -I & 0 & 0 \\ * & * & * & * & * & * & * & -I & 0 \\ * & * & * & * & * & * & * & * & -\varepsilon I \end{bmatrix} < 0 \tag{4}$$

where $\Phi_1 = PA+PBKC+(PA+PBKC)^T-Y-Y^T+Q$, $\Phi_2 = PA_1+Y-W^T$, $\Phi_3 = W+W^T-(1-\mu)Q$, $\Gamma = \varepsilon[N^T+(KC)^TN_b^T][N^T+(KC)^TN_b^T]^T$, $\Psi = \varepsilon[N^T+(KC)^TN_b^T]N_1$, then there exists a γ-suboptimal H_∞ controller for all time delay satisfying $0 < \tau(t) < \overline{\tau}$ and $\dot{\tau}(t) \leqslant \mu$.

3. Computational Algorithm

The matrix inequality condition in Theorem 1 is not an LMI in terms of the decision matrix variables. An iterative algorithm has been used to solve (4) in most of the published works. However, only local solutions can be found and only state feedback controllers can be obtained (i.e., the matrix C is invertible in (1)). In the following, an algorithm which combines the random search capability of GA with the solvability of LMI will be proposed. Specifically, we find a desirable controller K by solving the following maximization problem:

$$\max_{K\in\mathbb{R}^{m\times p}} \overline{\tau} \text{ subject to LMI (4)} \tag{5}$$

In this problem, GA is used to randomly generate a matrix $K \in \mathbb{R}^{m\times p}$ initially which changes thereafter within the evolution procedure according to objective (5). If (5) is feasible for an evolved K, which has the maximum $\overline{\tau}$, then this K satisfies the specifications and thus constitutes a solution to the design problem. Note that the matrix inequality (4) is LMI once the control gain matrix K is known, and this LMI can be solved efficiently by using efficient convex optimization algorithm. Furthermore, nonsquare matrix C cannot affect the characteristic of LMI in (4) so that the static output feedback controller can be designed as well by defining an appropriate C matrix.

As the standard GAs can be found in most related textbooks, an outline of our algorithm, which is similar to that used in [10], is given below:

Step 1. Use a binary string to encode the feedback gain matrix K.

Step 2. Generate randomly an initial population of N_p individuals.

Step 3. Evaluate the objective (5) and assign fitness to every individual. Decode the initial population produced in *Step 2* into real values for every controller gain matrix K_j, $j = 1, 2, \ldots, N_p$. For every K_j, use the bisection method to search for the maximum delay τ_j such that with such a delay τ_j and K_j, LMI (4) is feasible. Take every delay τ_j as the objective value corresponding to K_j and associate every K_j with a suitable fitness value according to rank-based fitness assignment approach, and then go to *Step 4*. If for a K_j, there is no feasible delay can be found such that LMI (4) is feasible, the objective value corresponding to K_j will be assigned a large value to reduce its opportunity to be survived in the next generation.

Step 4. Use tournament selection approach to choose the offspring.

Step 5. Perform uniform crossover with probability p_c to produce new offspring.

Step 6. Mutate bits for individuals in the population with a small mutation probability p_m.

Step 7. Retain the best chromosomes in the population with elitist reinsertion method.

Steps 3–7 correspond to one generation. The evolution process will repeat for N_g generations or being ended when the search process converges with a given accuracy. The best chromosome is decoded into real values to produce again the control gain matrix.

4. Numerical Examples

The basic GA parameters used in this paper are as follows: $N_p = 80$, $p_c = 0.8$, $p_m = 0.01$, $N_g = 30$. As GA is a probabilistic search procedure based on the mechanism of natural selection and natural genetics, to show a fair evaluation, in the following, we will carry out 50 runs independently for every case.

Example 1. Consider the example as appeared in [1–7] with the following system matrices:

$$A = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}, \quad A_1 = \begin{bmatrix} -1 & -1 \\ 0 & 0.9 \end{bmatrix}, \quad B_w = \begin{bmatrix} 1 \\ 1 \end{bmatrix},$$
$$B = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \quad C_0 = \begin{bmatrix} 0 & 1 \end{bmatrix}, \quad D = 0.1, \quad D_w = 0$$

As considered in the aforementioned references, the time delay is constant and hence $\mu = 0$.

In terms of the given H_∞ performance bound γ, the C matrix, and the search range for the controller gain, we search for the maximal delay size for several cases using the algorithm (referred to the "GA approach" in the sequel) presented in the last section. The statistical results for 50 runs are given in Table 1, where the percentages within the brackets indicate the probabilities of the obtained values in the 50 runs, *i.e.*, each percentage in the bracket represents the percentage of solutions that gives minima/maxima and the number of all the feasible solutions in each of the 50 runs. In the table, "not found" means that, for such a combination of performance and delay size, a solution may not exist or if exists, the algorithm cannot find it in the computational setting. Fig. 1 shows the evolution process of the maximal delay for 50 runs when $\gamma = 0.1015$, $C = I_{2\times 2}$. It can be seen from Fig. 1 that every run can converge to a stable value within 30 generations.

The results listed in Table 1 are obtained based on certain specified search ranges for the controller gains. In fact, under the same H_∞ performance bound γ, different search range will affect the obtained maximal delay. For

Figure 1. Evolution process for the maximal time delay within 50 runs, $\gamma = 0.1015$.

Table 1
Statistical Results of GA Approach with 50 Runs: Example 1

γ	$\overline{\tau}$		C Matrix	Search Range
	Minimum	Maximum		
0.1015	1.3908 (2.04%)	1.4137 (22.45%)	$I_{2\times 2}$	[−800 800]
0.1015	Not found	Not found	[1 0]	[−800 800]
0.1015	1.4134 (61.7%)	1.4137 (38.3%)	[0 1]	[−800 800]
0.1287	1.4137 (100%)	1.4137 (100%)	$I_{2\times 2}$	[−40 40]
0.1287	Not found	Not found	[1 0]	[−400 400]
0.1287	1.4137 (100%)	1.4137 (100%)	[0 1]	[−40 40]
19.12	36.7195 (2.33%)	68.7248 (2.33%)	$I_{2\times 2}$	[−100 100]
19.12	0.8991 (2%)	0.9873 (80%)	[1 0]	[−800 800]
19.12	1.4137 (100%)	1.4137 (100%)	[0 1]	[−100 100]

Table 2
Statistical Results of GA Approach with Different Search Range in 50 runs

γ	$\overline{\tau}$		Feedback Gain Matrix K	Search Range
	Minimum	Maximum		
0.1287	1.4138 (2%)	1.4140 (98%)	$10^3[-0.0002 \quad -1.3734]$	$[-10^4 \quad 10^4]$
0.1287	1.4130 (4%)	1.4142 (46%)	$10^5[-0.0001 \quad -5.2260]$	$[-10^6 \quad 10^6]$
0.1287	5.0002 (4%)	8.7503 (2%)	$10^7[0.0193 \quad -8.8135]$	$[-10^8 \quad 10^8]$

Table 3
Comparison of Maximal $\overline{\tau}$ Allowed (State Feedback)

Methods	Given γ	Maximal $\overline{\tau}$ Allowed	Feedback Gain Matrix K	C Matrix
Lee *et al.* [5]	0.1015	0.999	$[3.6828 \quad -827.0898]$	$I_{2\times 2}$
GA approach	0.1015	1.4137	$[-0.0023 \quad -519.5111]$	$I_{2\times 2}$
Fridman and Shaked [3]	0.1287	0.999	$[0 \quad -1.0285\times 10^6]$	$I_{2\times 2}$
Lee *et al.* [5]	0.1287	1.25	$[0.6407 \quad -89.1149]$	$I_{2\times 2}$
Xu *et al.* [7]	0.1287	1.39	$[-0.1120 \quad -74.1909]$	$I_{2\times 2}$
GA approach	0.1287	1.4137	$[-0.0010 \quad -8.5979]$	$I_{2\times 2}$
Palhares *et al.* [6]	19.12	6	$[-279.35 \quad -343.6300]$	$I_{2\times 2}$
GA approach	19.12	68.7248	$[-99.1695 \quad -99.4198]$	$I_{2\times 2}$

example, when $\gamma = 0.1287$, we search for the state feedback controller within different search range. The results are given in Table 2 from which we can see that under the same performance bound γ, a larger controller gain is necessary to ensure a larger delay bound for the same system.

To illustrate the reduced conservatism of the obtained results, we compare the optimal results for the state feedback cases obtained in Table 1 with previous results in Table 3. We note that the results published in [7] are less conservative than previous results as the improved matrix inequalities are used (the result for [7], computed using the suggested iterative method, was not reported in the paper). However, the H_∞ synthesis result in [7] is still based on the iterative algorithm. It can be seen from Table 3 that for the same performance bound γ, the GA approach can find the state feedback controllers that allow larger delay size than existing methods. In this sense, the GA approach is less conservative than the methods compared. The GA approach is based on the improved matrix inequalities presented in [7], but the obtained results are much less conservative than those reported. This shows that the GA approach has reduced the conservatism caused by using the iterative algorithm. Furthermore, it is noted that the state feedback gains obtained by the GA approach are all smaller than the corresponding ones presented in [5–7] as we naturally constrain the search range for the controller gains in the GA approach. A smaller controller for the same γ will reduce the possibility of input saturation.

Part of the optimal results obtained in Table 1 for the static output control cases are listed in Table 4. It is observed that even for some obtained static output feedback controllers, they can also allow larger delay size than the previous results for the state feedback controllers under the same performance bound in spite of their simplicity.

Table 4
Optimal Results for Maximal $\overline{\tau}$ Allowed (Static Output Feedback)

Given γ	Maximal $\overline{\tau}$ Allowed	Feedback Gain Matrix K	C Matrix
0.1015	1.4137	−367.6754	[0 1]
0.1287	1.4137	−8.2885	[0 1]
19.120	0.9873	0.1060	[1 0]
19.120	1.4137	−0.8004	[0 1]

Example 2. Now, consider the system matrices as:

$$A = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}, \quad A_1 = \begin{bmatrix} -1 & -1 \\ 0 & 0.9 \end{bmatrix}, \quad B_w = \begin{bmatrix} 1 \\ 1 \end{bmatrix},$$

$$B = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \quad C_0 = \begin{bmatrix} 0 & 1 \end{bmatrix}, \quad D = 0, \quad D_w = 0,$$

$$M = \begin{bmatrix} 0.2 & 0 \\ 0 & 0.2 \end{bmatrix}, \quad N = N_1 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad N_b = \begin{bmatrix} 0 \\ 0 \end{bmatrix}.$$

Notice that $\| \triangle A(t)\| \leqslant 0.2$, $\| \triangle A_1(t)\| \leqslant 0.2$. This case has also been studied in [1, 3, 5–7].

Table 5
Statistical Results of GA Approach with 50 Runs: Example 2

γ	$\overline{\tau}$		C Matrix	Search Range
	Minimum	Maximum		
0.03	1.3512 (5.41%)	1.3527 (72.97%)	$I_{2\times 2}$	$[-90 \quad 90]$
0.03	Not found	Not found	[1 0]	$[-900 \quad 900]$
0.03	1.0384 (100%)	1.0384 (100%)	[0 1]	$[-90 \quad 90]$
0.01	1.3481 (2%)	1.3512 (12%)	$I_{2\times 2}$	$[-90 \quad 90]$
0.01	Not found	Not found	[1 0]	$[-900 \quad 900]$
0.01	1.0378 (100%)	1.0378 (100%)	[0 1]	$[-90 \quad 90]$

Figure 2. Evolution process for the maximal time delay within 50 runs, $\gamma = 0.03$.

As in Example 1, the maximal delay sizes for several cases are searched using the GA approach in terms of a given H_∞ performance bound γ for different C matrices. The statistical results for 50 runs are given in Table 5. Fig. 2 shows the evolution process of the maximal delay for 50 runs when $\gamma = 0.03$, $C = I_{2\times 2}$.

To illustrate the reduced conservatism of the obtained results, we compare the optimal results for the state feedback cases obtained in Table 5 with previous results in Table 6. It can be seen from Table 6 that even for the case of $\gamma = 0.01$, $\overline{\tau} = 1.3512$, a desired robust H_∞ state feedback controller can be computed as $[-33.4319 \quad -73.3984]$ using the GA approach. This controller achieves a much smaller γ for much bigger $\overline{\tau}$ which implies that the GA approach is much more effective than the existing methods.

Part of the optimal results obtained in Table 5 for the static output control cases are listed in Table 7. It is again observed that the static output feedback controllers can allow larger delay size than the previous results for the state feedback controllers under the same performance.

5. Conclusion

This paper presents an algorithm for designing robust H_∞ controllers for uncertain time-delay systems. By using a GA to search for possible controller gains and solving an

Table 7
Optimal Results for γ-*Suboptimal* H_∞ *controller* (Static Output Feedback)

γ	$\overline{\tau}$	Feedback Gain Matrix K	C Matrix
0.03	1.0384	-33.6042	[0 1]
0.01	1.0378	-55.8804	[0 1]

Table 6
Comparison of γ-*Suboptimal* H_∞ *Controller* (State Feedback)

Methods	γ	$\overline{\tau}$	Feedback Gain Matrix K	C Matrix
de Souza and Li [1]	1.95	0.3	Not provided	$I_{2\times 2}$
Lee *et al.* [5]	0.05	0.8	$[-0.0337 \quad -64.9821]$	$I_{2\times 2}$
Xu *et al.* [7]	0.03	0.9	$[0.2536 \quad -99.0807]$	$I_{2\times 2}$
GA approach	0.03	1.3527	$[-29.9264 \quad -65.6218]$	$I_{2\times 2}$
GA approach	0.01	1.3512	$[-33.4319 \quad -73.3984]$	$I_{2\times 2}$

LMI, the required controller can be determined. Moreover, appropriate structural constraints can be imposed on the controllers. Based on the recently developed matrix inequality condition, the proposed approach reduces the conservatism resulting from the iterative algorithm when designing for the H_∞ controller. The improvement over previous methods by allowing a larger delay size under the same H_∞ performance bound has been demonstrated via numerical examples.

References

[1] C.E. de Souza & X. Li, Delay-dependent robust H_∞ control of uncertain linear state-delayed systems, *Automatica*, *35*, 1999, 1313–1321.

[2] Y.S. Lee, Y.S. Moon, & W.H. Kwon, Delay-dependent guaranteed cost control for uncertain statedelayed systems, In *Proc. American Control Conference*, 2001, 3376–3381.

[3] E. Fridman & U. Shaked, A descriptor system approach to H_∞ control of linear time-delay systems, *IEEE Transactions on Automatic Control*, *47*(2), 2002, 253–270.

[4] H. Gao & C. Wang, Commments and further results on a descriptor system approach to H_∞ control of linear time-delay systems, *IEEE Transactions on Automatic Control*, *48*(3), 2003, 520–525.

[5] Y.S. Lee, Y.S. Moon, W.H. Kwon, & P.G. Park, Delay-dependent robust H_∞ control for uncertain systems with a state-delay, *Automatica*, *40*, 2004, 65–72.

[6] R.M. Palhares, C.D. Campos, P.Y. Ekel, M.C.R. Leles *et al.*, Delay-dependent robust H_∞ control of uncertain linear systems with lumped delays, *IEE Proceedings: Control Theory and Applications*, *152*(1), 2005, 27–33.

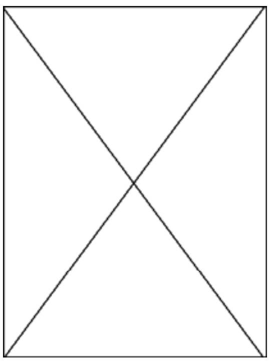
[7] S. Xu, J. Lam, & Y. Zou, New results on delay-dependent robust H_∞ control for systems with time-varying delays, *Automatica*, *42*, 2006, 343–348.

[8] V. Oduguwa, A. Tiwari, & R. Roy, Evolutionary computing in manufacturing industry: An overview of recent applications, *Applied Soft Computing*, *5*(3), 2005, 281–299.

[9] T. Mantere & J.T. Alander, Evolutionary software engineering, a review, *Applied Soft Computing*, *5*(3), 2005, 315–331.

[10] H. Du, J. Lam, & K.Y. Sze, Non-fragile output feedback H_∞ vehicle suspension control using genetic algorithm, *Engineering Applications of Artificial Intelligence*, *16*(8), 2003, 667–680.

Biographies



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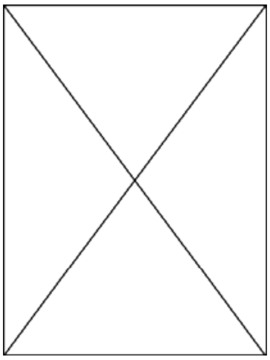

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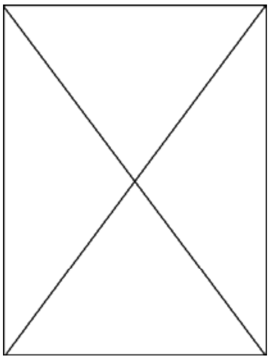

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