Journal of ELECTRICAL ENGINEERING, VOL. 55, NO. 9-10, 2004, 251–255

FUZZY MODELLING AND ADAPTIVE CONTROL OF UNCERTAIN SYSTEM

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A simple and systematic approach is developed for modelling and adaptive control of an unknown or uncertain system, using only input-output data obtained from the underlying dynamical system. Gaussian fuzzy membership functions are used in conjunction with the least-squares principle for the modelling and control. Based on the fuzzy modelling, an adaptive controller is devised which works through the self-adjusting vector of the controller parameters. The effectiveness of the proposed design procedure is illustrated using the generator as a simple example.

K e y w o r d s: adaptive fuzzy control, adaptation, uncertain system, nonlinear systems, fuzzy logic.

1 INTRODUCTION

Intelligent control techniques, such as fuzzy control, have been developed in attempt to emulate human operators. Whether or not they can really work like humans remains as a major question for further research; yet various paradigms that are currently available in the literature have provided a new dimension for modelling and approximation of complex systems and processes. On the other hand, the motivation for using fuzzy systems and fuzzy control stems in part from the fact that it is particularly suitable in the industrial processes when the physical systems or quality criteria are too complex to model. This modelling and control technique creates a control surface by combining rules with fuzzy sets; it even allows designers to build fuzzy controller when their understanding of the system is incomplete, or only system input-output data but no model structure is available for the design. Some existing successful methods and techniques have been reviewed in [1–5].

In this paper, we are looking into the possibility of developing a simple fuzzy system type of intelligent mechanism that can be used to model a system and then to control it to a desired target, using only input-output data obtained from an unknown (or uncertain) underlying system. Section 2 introduces the fuzzy modelling based on the least-squares approach incorporating the Gaussian type fuzzy membership functions. Only the system input-output data are needed for the modelling. Based on this model, a fuzzy adaptive controller is developed in Section 4. Section 5 gives, in a constructive manner, the steps for constructing the adaptive fuzzy controller. Some simulation results are given in Section 6. The paper in concluded by Section 7.

2 FUZZY MODELLING

The basic design uses a fuzzy logic system constructed by variable fuzzy basis functions and an adaptive parameter vector, as an alternative of the unknown underlying dynamical system. Figure 1 shows the block diagram of the proposed fuzzy modelling and adaptive control scheme, where $\dot{x} = f(x,t)$ is the uncertain system to be controlled, x_d is the reference input, u is the control input, and x is the system output.

In our basic setup, the fuzzy set is characterized by a Gaussian membership function $\mu_f(x)$ defined over a set U, expressed as

$$\mu(x) = \exp\Big(-\frac{(x-\bar{x})}{2\sigma^2}\Big) \tag{1}$$

here $\bar{x}$ is the center of the membership function at which the membership grade is equal to 1, and $\sigma > 0$ is the spread of membership function. Let $x = [x_1, x_2, \dots, x_n]^\top$, where $x_1, x_2, \dots, x_n$ are known system variables, and define a fuzzy basis function by

$$p_j(x) = \frac{\prod_{i=1}^{n} \mu_{ij}(x_i)}{\sum_{j=1}^{m}\prod_{i=1}^{n} \mu_{ij}(x_i)} \qquad j = 1, 2, \dots, m \tag{2}$$

where $\mu_{ij}(x_i)$ is the Gaussian membership function of a fuzzy set to be used in the modelling, and m is the number of used fuzzy rules. Then a continuous function on a bounded set U can be uniformly approximated by

$$f(x) = \sum_{j=1}^{m} p_j(x)\theta_j \tag{3}$$

where θ_j are constant coefficients to be determined in the modelling. It can be verified that the set

$$F = \Big(f(x) \mid f(x) = \sum_{j=1}^{m} p_j(x)\theta_j\,; x \in U\Big) \tag{4}$$

satisfies the three conditions of the classical Stone-Weierstrass uniform approximation theorem [6]. This indicates that (3) is a good fuzzy model for constructing the underlying dynamical system.

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ISSN 1335-3632

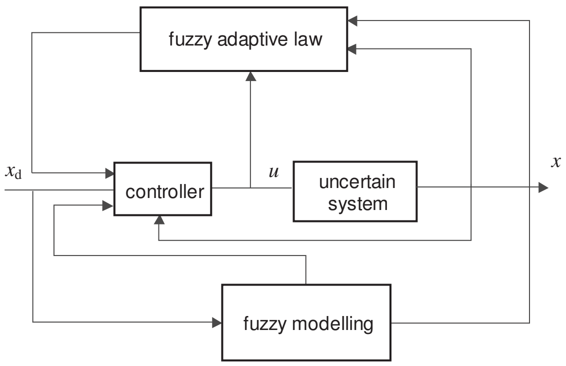

Fig. 1. Block diagram of the fuzzy adaptive control system

The defuzzifier maps a fuzzy set to a crisp point in R. We use the center-average defuzzifier mapping, *ie*,

$$y(x) = \frac{\sum_{j=1}^{m} \theta_j \left(\prod_{i=1}^{n} \mu_{ij}(x_i)\right)}{\sum_{j=1}^{m} \left(\prod_{i=1}^{n} \mu_{ij}(x_i)\right)} \,. \tag{5}$$

Equation (5) can be rewritten into the form

$$y(x) = \theta^\top \xi(x) \tag{6}$$

where

$$\theta = (\theta_1, \dots, \theta_m)^\top \tag{7}$$

is the parameter vector, and

$$\xi(x) = \left(\xi^1(x), \dots, \xi^m(x)\right)^\top \tag{8}$$

is the regressive vector with the regressor defined by

$$\xi^l(x) = \frac{\prod_{i=1}^{n} \mu_{ij}(x_i)}{\sum_{j=1}^{m} \left(\prod_{i=1}^{n} \mu_{ij}(x_i)\right)} \,, \qquad j = 1, 2, \dots, m \,. \tag{9}$$

When (6) is used to model the unknown system, we need to determine two parameter vectors, $\xi(x)$ and θ, in this fuzzy model. Since we use Gaussian membership functions (1), the estimation of fuzzy basis functions $\xi(x)$ becomes to estimate the means and variances of the Gaussian membership functions.

3 PLANT MODEL AND CONTROL OBJECTIVE

Consider a class of nonlinear dynamical systems modelled by the differential equation

$$x^{(n)} = f(x) + bu \,. \tag{10}$$

where $x = \begin{bmatrix} x & \dot{x} & \dots & x^{(n-1)} \end{bmatrix}^\top$ is the state vector, u is the control input, the function $f = f(x)$ is unknown to us. Let $x_d = x_d(t) = \begin{bmatrix} x_d(t) & \dot{x}_d(t) & \dots & x_d^{(n-1)}(t) \end{bmatrix}^\top$ denote the desired state trajectory and let $e = x - x_d = \begin{bmatrix} e & \dot{e} & \dots & e^{(n-1)} \end{bmatrix}^\top$. We wish to construct a controller u such that $\lim_{t\to\infty} e(t) = 0$.

4 CONTROL LAW DEVELOPMENT

Assume that $f(x)$ is unknown. We approximate $f(x)$ using the fuzzy logic system $\theta^\top \xi(x)$. Let θ^* be the "optimal" constant vector such that

$$\theta^* = \arg\min_{\theta} \sup_{x\in\Omega} \left| f(x) - \theta^\top \xi(x) \right| \tag{11}$$

where $\Omega \subseteq R^n$ is a region in which the state x is constrained to reside. We assume that

$$\left| f(x) - \theta^{*\top} \xi(x) \right| \le d \qquad \forall\, x \in \Omega \tag{12}$$

where $d > 0$ and each element of θ^* is a constant and bounded below and above as follows

$$\underline{\theta}_i \le \theta_i \le \overline{\theta}_i \qquad \forall i = 1, \dots, r \tag{13}$$

or in vector notation

$$\underline{\theta} \le \theta \le \overline{\theta} \,. \tag{14}$$

We assume that the lower and upper bounds are known. This assumption may seem unrealistic and restrictive. However, one can just choose rough bounds based on experience or any knowledge about the nonlinearity.

Let us define the adaptation parameter error as

$$\phi = \theta - \theta^* \,. \tag{15}$$

To proceed, let us analyze the tracking error dynamics.

The tracking error dynamics can be rewritten as

$$\begin{aligned} \dot{e} &= \begin{bmatrix} 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 1 & 0 & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & & \dots & & 0 \end{bmatrix} e + \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix} \left(x^{(n)} - x_d^{(n)}\right) \\ &= Ae - b_c ke + b_c ke + b_c\left(x^{(n)} - x_d^{(n)}\right) \\ &= \left(A - b_c k\right)e + b_c\left(ke + f + bu - x_d^{(n)}\right) \end{aligned} \tag{16}$$

where k is chosen so that $A_m = A - b_c k$ is asymptotically stable.

System $f(x)$ can be expressed as

$$\begin{aligned} \hat{f}(x) = \theta^\top \xi(x) &= \sum_{j=1}^{m} \frac{\theta_j \left(\prod_{i=1}^{n} \mu_{ij}(x_i)\right)}{\sum_{j=1}^{m} \left(\prod_{i=1}^{n} \mu_{ij}(x_i)\right)} \\ &= \sum_{j=1}^{m} \frac{\theta_j \left(\prod_{i=1}^{n} \exp\left[-\frac{1}{2}\left(\frac{x_i - \bar{x}_{ij}}{\sigma_{ij}}\right)^2\right]\right)}{\sum_{j=1}^{m} \left(\prod_{i=1}^{n} \exp\left[-\frac{1}{2}\left(\frac{x_i - \bar{x}_{ij}}{\sigma_{ij}}\right)^2\right]\right)} \,. \end{aligned} \tag{17}$$

During the on-line adaptation, σ_{ij} and $\bar{x}_{ij}$ are fixed while θ_j are to be estimated. After each on-line adaptation we have a new approximate model at each sampled time along with a new estimated θ. Equation (6) will become a standard linear least-squares problem if the fuzzy basis function $\xi(x)$ is fixed at each step. There are many algorithms available for estimating the best θ, which minimizes the index

$$E_\theta = \sum_{i=1}^{t} \lambda^{t-i} \Big[f(i) - \hat{f}(i)\Big]^2 \tag{18}$$

where $\lambda \in (0,1]$ is a forgetting factor. θ can be updated by this minimization.

We use the following recursive least-squares error formulas to update θ

$$\varphi(t) = \frac{1}{\lambda}\big[\varphi(t-1) - \varphi(t-1)\xi\big(x(t)\big)\big(\lambda + \xi^\top\big(x(t)\big)\varphi(t-1)\xi\big(x(t)\big)\big)^{-1}\xi^\top\big(x(t)\big)\varphi(t-1)\big] \tag{19}$$

$$k(t) = \varphi(t-1)\xi\big(x(t)\big)\big[\lambda + \xi^\top\big(x(t)\big)\varphi(t-1)\xi\big(x(t)\big)\big]^{-1} \tag{20}$$

$$\theta(t) = \theta(t-1) + k(t)\big[\hat{f} - \xi^\top\big(x(t)\big)\theta(t-1)\big] \tag{21}$$

$t = 1, 2, \dots$. Matrix φ is initialized to be $\varphi(0) = \beta I$, where I is the $m \times m$ identity matrix and β is a small positive constant.

We define $V = \frac{1}{2}e^\top Pe$, where P is a symmetric positive definite matrix satisfying the Lyapunov equation

$$A_m^\top P + PA_m = -Q \tag{22}$$

where $Q > 0$.

We use the following fuzzy adaptation control law

$$u = u_c + u_s \tag{23}$$

where u_s satisfies the following conditions

$$\begin{aligned} &\sigma\big(ke + f + b(u_s + u_c) - x_d^{(n)}\big) \le \varepsilon \\ &\sigma u_s \le 0 \end{aligned} \tag{24}$$

where $\varepsilon > 0$ is a designer parameter. There are several different ways to select u_s so that it satisfies (24).

ASSUMPTION 1. We can determine functions $f^M(x)$ and b_m such that $|f(x)| \le f^M(x)$ and $0 < b_L \le b$, *ie* we assume that we know the upper bound of $|f(x)|$ and the lower bound of b.

We construct the supervisory control u_s as follows [7, 8]

$$u_s = -\operatorname{sign}\big(x^\top Pb_c\big)\Big[\frac{1}{b_m}\big(f^M + |k^\top x| + |u_c|\big)\Big]. \tag{25}$$

Control u_c is a basic control [9]

$$u_c = \frac{1}{b}\big(-\theta^\top\xi + x_d^{(n)} - ke\big). \tag{26}$$

We now proceed to analyze the dynamics of the tracking error.

DEFINITION 1. The tracking error e is uniformly ultimately bounded (UUB) with respect to a closed ball $\bar{B}$ if for every $d > 0$, there exists $T(d)$ such that if $\|e(t_0)\| \le d$, then $e(t) \in \bar{B}$ for $t \ge t_0 + T(d)$.

THEOREM 1. *Consider the closed-loop system*

$$\begin{aligned} x^{(n)} &= f(x) + bu \\ u &= u_c + u_s \\ \dot{\theta}(t) &= \theta(t-1) + k(t)\Big[\hat{f} - \xi^\top\big(x(t)\big)\theta(t-1)\Big] \end{aligned} \tag{27}$$

where u_s satisfies (24). Then, we have

(i) $e^\top(t)Pe(t) \le \exp\big(-\mu t\big)e^\top(0)Pe(0) + \frac{\varepsilon}{\mu}$ *where* $\mu = \frac{\lambda_{\min}(Q)}{\lambda_{\max}(P)}$,

(ii) *the tracking error e is UUB with respect to any ball of radius greater than* $\sqrt{\frac{\lambda_{\min}(P)}{\lambda_{\max}(P)}}R$, *that is, if* $\|e_0\| \le d$, *then for given* $\tilde{b} > \sqrt{\frac{\lambda_{\max}(P)}{\lambda_{\min}(P)}}R$, $\|e(t)\| \le \tilde{b}$ *for all* $t \ge t_0 + T\big(\tilde{b}, d\big)$, *where* $R = \sqrt{\frac{\varepsilon}{\lambda_{\min}(Q)}}$, $T(d) = \begin{cases} 0 & d \le \tilde{R} \\ \frac{\lambda_{\max}(P)d^2 - \lambda_{\min}(P)\tilde{R}^2}{\lambda_{\min}(Q)\tilde{R}^2 - \varepsilon} & d > \tilde{R} \end{cases}$ *and $\tilde{R}$ is obtained from the equation* $\lambda_{\max}(P)\tilde{R}^2 = \lambda_{\min}(P)\tilde{b}^2$,

(iii) *if there exists θ^* such that $f(x) = \theta^{*\top}\xi(x)$, then the origin of the $[e \quad \phi]$-space is stable and hence e and ϕ are bounded and $e(t) \to 0$ as $t \to \infty$.*

P r o o f . See Appendix.

From (i) of the above theorem and the expression for u_s we can see that the design parameter ε determines the final accuracy of the tracking error that can be made arbitrarily small. As expected, the smaller the desired tracking error, the larger the controller's gain required, that is, the tracking error can be made arbitrarily small by increasing the controller's authority. The trade-off between the steady-state tracking error and the control effort is expressed by the radius of the uncertainty ball

$$\Big\{e\colon \|e\| \le \sqrt{\frac{\varepsilon}{\mu\lambda_{\min}(p)}}\Big\}, \tag{28}$$

the above expression is obtained from (ii). We call the above set uncertainty ball because the tracking error is guaranteed to enter the ball after finite time and reside within this ball thereafter. Note that the expression of the ball given by (28) can be obtained from (i) of Theorem 1 by letting $t \to \infty$ and using the relationship $\lambda_{\min}(P)\|e(t)\|^2 \le e^\top(t)Pe(t)$.

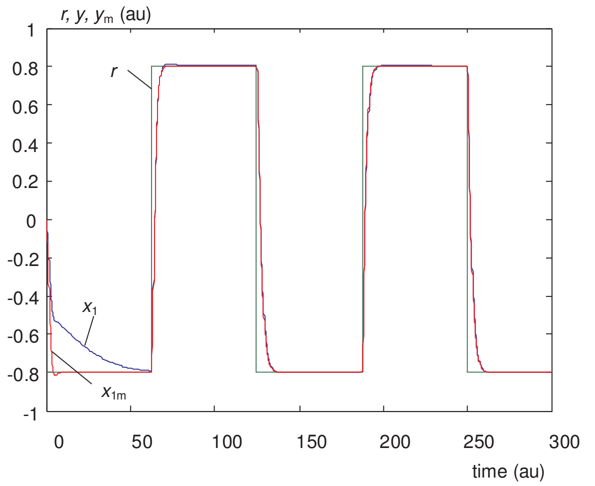

Fig. 2. The time-response of trajectory x_1 (solid line) its desired reference model value $y_m(t)$ (dashed line) and reference signal (dashed and dotted line)

5 FUZZY ADAPTIVE CONTROLLER DESIGN

It is much easier to introduce the adaptive controller design procedure by working through a specific example than giving a general description. Consider the uncertain system

$$\begin{aligned} \frac{\mathrm{d}\delta}{\mathrm{d}t} &= \omega\,, \\ \frac{\mathrm{d}\omega}{\mathrm{d}t} &= \frac{1}{M}\big(P_m - P_{\max}\sin\delta - D\omega\big)\,. \end{aligned} \tag{29}$$

Let

$$a_2 = \frac{D}{M}\,, \qquad a_1 = \frac{1}{M}\,, \qquad b = \frac{1}{M}\,. \tag{30}$$

Let $(\delta_0, 0)$ be an equilibrium point of nonlinear system (29), where δ_0 is a solution of equation $P_{\max}\sin\delta = P_m$. The Lyapunov stability theorem requires the system in form where equilibrium point is $(0,0)$. It can be obtained by simple transformation of state variables $x_1 = \delta - \delta_0$, $x_2 = \omega$. Transformed state space equations are

$$\begin{aligned} \dot{x}_1 &= x_2\,, \\ \dot{x}_2 &= -a_2 x_2 - a_1 \sin x_1 + bu\,. \end{aligned} \tag{31}$$

The control problem is to design u to control the system state $(x_1 \quad x_2)^\top$ to track a desired state $(x_{1d} \quad x_{2d})^\top$. Using the tracking error

$$e = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} - \begin{pmatrix} x_{1d} \\ x_{2d} \end{pmatrix} = \begin{pmatrix} e_1 \\ e_2 \end{pmatrix} \tag{32}$$

we construct a Lyapunov function candidate

$$V_1(e_1, e_2) = \frac{1}{2}(e_2 + e_2)^2 \tag{32}$$

which, considering that $e_1 \equiv -e_2$ is unlikely in practice, gives

$$\dot{V}_1(e_1, e_2) = (e_1 + e_2)(\dot{e}_1 + \dot{e}_2)\,. \tag{34}$$

To verify the design approach, several simulation examples have been tested: In all these simulations $M = 0.03$, $D = 0.1$ and $P_{\max} = 1$. The reference model has been chosen as follows

$$\begin{aligned} \dot{x}_{m1} &= x_{m2}\,, \\ x_{m2} &= -2x_{m1} - 3x_{m2} + 2r \end{aligned} \tag{35}$$

where r is the reference signal. We have used the sharp square signal generator with amplitude 0.8 and frequency 0.008 Hz.

6 SIMULATION RESULTS

The tracking result is shown in Fig. 2, which is quite satisfactory. Figure 2 is the simulation with noise (the mean equals zero and the standard variance equals one) added to the system. It shows that the fuzzy adaptive control scheme is effective in controlling the generator system with partial knowledge. Theoretical and simulation results have both proven that this control approach is robust and stable.

7 CONCLUSION

A fuzzy modelling and adaptive fuzzy control scheme has been developed and applied to an uncertain system. The tracking control results are quite satisfactory. The simulation results have shown that this control approach is robust and stable. The method can be further extended to handle some other uncertain nonlinear and chaotic dynamical systems since this technique in principle suggests a general approach.

By using RLS training method, minimization generally converges very fast while achieving very accurate fuzzy modelling. It is more convenient to apply this control method in real applications.

Appendix Proof of Theorem 1

To prove (i), we consider $V = \frac{1}{2}e^\top Pe$. The time derivative of V evaluated on the solutions of the closed-loop system (10), (23) is

$$\dot{V} = e^\top P\dot{e} = -e^\top Qe + e^\top Pb_c\big(ke + f + bu - x_d^{(n)}\big)\,. \tag{A.1}$$

Substituting into the above equation the expression for the control law given by (23) and applying (24) gives

$$\begin{aligned} \dot{V} &= -e^\top Qe + \sigma\big(ke + f + b(u_c + u_s) - x_d^{(n)}\big) \\ &\le -e^\top Qe + \varepsilon \le -\lambda_{\min}(Q)\|e\|^2 + \varepsilon \\ &\le -\frac{\lambda_{\min}(Q)}{\lambda_{\max}(P)} e^\top Pe + \varepsilon = -\mu V + \varepsilon \end{aligned} \tag{A.2}$$

where $\mu = \frac{\lambda_{\min}(Q)}{\lambda_{\max}(P)}$. Invoking now the Comparison lemma [7], we obtain (i).

To prove (ii), we let $e(t, t_0, e_0)$ to denote the tracking error e at time t subject to the initial condition $e(t_0) = e_0$. If $d \le \tilde{R}$, then $\|e(t)\| \le \tilde{b}$ for all $t \ge t_0$. Hence $T(d) = 0$. On the other hand, if $d > \tilde{R}$, we prove by contradiction that there exists $t_1 \in [t_0, t_0 + T(d)]$ such that $\|e(t_1)\| \le \tilde{R}$. Assume that $\|e(t)\| > \tilde{R}$ for all $t \in [t_0, t_0 + T(d)]$, and note that $\lambda_{\min}(Q)\|e\|^2 - \varepsilon \ge 0$ for $\|e\| > R$. Then we have

$$\begin{aligned}
&\lambda_{\min}(P) \left\|e\big(t_0 + T(d)\big); t_0, e_0\right\|^2 \\
&\qquad \le e^\top\big(t_0 + T(d)\big) P e\big(t_0 + T(d)\big) \\
&\qquad = e^\top(t_0) P e(t_0) + \int_{t_0}^{t_0+T(d)} \dot{V} \mathrm{d}t \\
&\qquad \le \lambda_{\max}(P)\, \|e(t_0)\|^2 - \int_{t_0}^{t_0+T(d)} \big(\lambda_{\min}(Q)\tilde{R}^2 - \varepsilon\big) \mathrm{d}t \\
&\qquad \le \lambda_{\max}(P) d^2 - \big(\lambda_{min}(Q)\tilde{R}^2 - \varepsilon\big) T(d) \\
&\qquad = \lambda_{\min}(P)\tilde{R}^2 \qquad \text{(A.3)}
\end{aligned}$$

which would imply that $\left\|e\big(t_0 + T(d)\big)\right\| \le \tilde{R}$. However, this contradicts the assumption that $\|e(t)\| > \tilde{R}$ for all $t \in [t_0, t_0 + T(d)]$. Thus, for some $t_1 \in [t_0, t_0 + T(d)]$, $\|e(t_1)\| \le \tilde{R}$ and we can conclude that $\|e\| \le \tilde{b}$ for all $t \ge t_1$ by referring to the case when $d \le \tilde{R}$.

To prove (iii), we consider the following Lyapunov function candidate

$$V = \frac{1}{2}\big(e^\top P e + \phi^\top \phi\big). \qquad \text{(A.4)}$$

By assumption, $f = \theta^\top \xi$ as well as condition (24) hold. In addition, it follows from (23) that $x_d^{(n)} - ke = \theta^\top \xi$. Taking into account all of the above in evaluating the time derivative of V on the trajectories of the closed-loop system (27), we obtain

$$\begin{aligned}
\dot{V} &= e^\top P \dot{e} + \phi^\top \phi \\
&\le -e^\top Q e + \sigma b u_s \le -e^\top Q e \le -\frac{\lambda_{\min}(Q)}{\lambda_{\max}(P)} e^\top P e \\
&= -\mu e^\top P e. \qquad \text{(A.5)}
\end{aligned}$$

It follows from the above that the closed-loop system (27) is stable, and therefore, $e(t)$ and ϕ are bounded for $t \ge 0$.

To show that $e \to 0$ as $t \to \infty$, we integrate (A.5) to obtain

$$\int_0^t \dot{V}(\tau)\mathrm{d}\tau = V(t) - V(0) \le \int_0^t \big(-\mu e^\top P e\big)\mathrm{d}\tau \qquad \text{(A.6)}$$

or equivalently

$$\int_0^t \mu e^\top P e \mathrm{d}\tau \le V(0) - V(t) \le V(0). \qquad \text{(A.7)}$$

Thus, $\lim_{t\to\infty} \int_0^t \big(e^\top P e\big)\mathrm{d}\tau$ exists and is finite. It follows from the first part of the theorem that $e^\top P e$ is bounded and since $\frac{\mathrm{d}}{\mathrm{d}t} e^\top P e \le -\mu e^\top P e + \varepsilon$, we conclude that $\frac{\mathrm{d}}{\mathrm{d}t} e^\top P e$ is also bounded. Therefore, $e^\top P e$ is uniformly continuous. By Barbalat's lemma, $e^\top P e \to 0$ as $t \to \infty$. This implies that the tracking error, $e(t) \to 0$ as $t \to \infty$, which concludes the proof of the theorem.

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Received 4 February 2004

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