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CMAC-Based Compensator for Limiting Bound Required in Supervisory Control Systems

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***Abstract*—In this paper, a novel cerebellar model articulation controller (CMAC)-Based compensator is proposed to limit bound required in supervisory control systems. There are two structures in the proposed schemes: one is supervisory controller and the other is the CMAC-Based compensator. The supervisory controller can ensure Lyapunov stability of the controlled system in the presence of significant plant uncertainties, if the perfect control is estimated. The CMAC is employed to learn the perfect control, but a model error will exist in the learning process. The object of CMAC-based compensator is to suppress this model error, so that the supervisory of can be rationalized for uncertain nonlinear systems. Finally, simulation results demonstrate that the CMAC-based compensator not only can limit the bound required in supervisory controllers, but also can significantly improve the control performance.**

***Keywords*—CMAC, Supervisory Control, and Lyapunov Stability.**

I. Introduction

The object of supervisory control is to drive the system into a reasonable region when the current control performance is not acceptable. Considerable research results have been reported for the application of adaptive fuzzy control techniques based on supervisory control [1][2]. In fact, those supervisory control approaches can also be said to be a robust control scheme. The first supervisory controller (SC) is addressed in [3] and many similar SCs are proposed to guarantee the initial control performance [4]-[9] under different original control mechanisms (the so-called main control [10]), such as fuzzy systems, neural networks, Cerebellar Model Articulation Controllers (CMAC) [11][12], genetic algorithms, self-tuning PID controller, etc. These supervisory control schemes have a promising advantage of requiring no prior knowledge of system dynamics. Nevertheless, a serious drawback of theses approaches is that the robust bounds of some system parameters must be anticipatable when implementing supervisory controllers to ensure the stability of the system. In fact, those bounds will be difficult to obtain while the system functions are unknown in practical applications.

In this paper, we propose to use a learning mechanism to learn the perfect control in the robust control structure so that the supervisory controller can be implemented in practical systems. The model error will exist in the learning process, so the CMAC-based compensator is employed to suppress this side effect happened in the supervisory control system. It should be noted that the learning mechanism used is for online learning. Thus, it is important that the learning mechanism must have a quick learning property. In our implementation, CMAC [11][12] acts as the learning mechanism because of its quick learning capability. In the literature, there are also some CMAC based supervisory control approaches [1][2][13]. Most of them are to use CMAC for taking the place of the fuzzy estimators in adaptive fuzzy control. In reference [1], CMAC acts as a traditional adaptive controller in their control law and a sliding control based supervisory controller is also proposed. The authors further proposed a fuzzy mechanism to ease the transition between the adaptive controller and the supervisory controller. It can be found that the problem of model errors and the moderation of the requirement of the system function bounds are not handled in the approach. In reference [2], the authors added a compensated controller in the control structure to reduce possible model errors. In their derivation, this compensated controller becomes an adaptive term for ensuring the Lyapunov stability. They further proposed a novel controller in reference [13] by using a recurrent CMAC for replacing the original CMAC, and they also considered the sliding control structure in the control law design. Their approaches indeed can have effects when there are model errors in estimators, but their approaches still need to estimate the bound of the sliding controller. However, the estimated bound will increase because its slope is absolutely positive in their design. So we propose the CMAC-based limited bound compensator in supervisory control to solve above problems. The proposed approach not only makes the supervisory control be realized easily for any practical systems but also can improve the control performance.

This paper is organized as follows. The supervisory control for a nonlinear system is considered in Section II. The basic concepts of CMAC are introduced in Section III. The CMAC-based limited bound compensator is discussed in Section IV. Simulations and conclusions are in Section V.

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II. SUPERVISORY CONTROL FOR NONLINEAR SYSTEMS

Consider an *n*th-order nonlinear system of the form

$$x^{(n)} = f(x, x', \cdots, x^{(n-1)}) + b(x, x', \cdots, x^{(n-1)})u + d$$
$$y = x \qquad , \qquad (1)$$

where *b* is an unknown but bounded continuous functions, *d* is an external bounded disturbance, and u and $y \in R$ are the input and the output of the system, respectively. Let $\hat{x} = (x, x', \cdots, x^{(n-1)}) \in R^n$ be the state vector of the system. The control objective is to force the system output to follow a given bounded reference signal *r* under the constraints that all signals involved must be bounded. Now, the task is to design a robust controller for an uncertain system and such a robust controller is designed to ensure the stability of the system in a Lyapunov sense.

First, consider that there is no disturbance in the system (i.e. *d*=0). It can be found that the system output can be ensured to approach to the reference signal *r*, if the control law is

$$u^* = \frac{1}{b}[r^{(n)} - f(x, x', \cdots, x^{(n-1)}) + \hat{k}^T \hat{e}] \qquad , \qquad (2)$$

where $\hat{k}$ and $\hat{e}$ are defined as $\hat{k} = [k_0, k_1, k_2, \cdots, k_{n-1}]^T$ and $\hat{e} = [e, e', e'', \cdots, e^{(n-1)}]^T$, and *e*(*t*) is the tracking error and is defined as $e(t) = r(t) - x(t)$. The controller in Equation (2) is usually referred to as the perfect control law. Now, apply the perfect control law to Equation (1) with *d*=0, and then we have

$$e^{(n)} + \hat{k}^T \hat{e} = 0 \quad . \qquad (3)$$

It is easy to verify that if $\hat{k}$ is selected such that the roots of the characteristic equation as Equation (3) are all in the open left-half plane, then the system will asymptotically track the reference input *r*.

Secondly, with the use of the Lyapunov stability theorem [14] [15], Theorem 1 is introduced to ensure the stability of supervisory control systems.

Theorem 1:

Consider the existence of uncertainties and external bounded disturbances (i.e., *d*≠0) in a control system. If a robust controller is considered as:

$$u = u^* + u_s, \qquad (4)$$

where the supervisory control u_s is defined as

$$u_s = sat(S / D_{\max}) \times D_{\max} = \begin{cases} D_{\max} & , for \quad S / D_{\max} \geq 1 \\ S & , for \quad -1 < S / D_{\max} < 1 \\ -D_{\max} & , for \quad S / D_{\max} \leq -1 \end{cases} ,$$

$$D_{\max} = \|d / b\|_\infty = \sup|d / b| = \frac{d^U}{b_L} , \qquad (5)$$

the lower bound of *b* is b_L ($0 < b_L \leq |b|$) and the upper bound of *d* is d^U ($|d| \leq d^U$), then the Lyapunov stability theorem will be satisfied.

Proofs:

Consider the Lyapunov function as

$$V_1 = \frac{1}{2} S^2 , \qquad (6)$$

where the sliding surface is defined as the integral of the characteristic polynomial,

$$S(t) = \int \dot{S}(t) dt \text{ , where } \dot{S}(t) = e^{(n)} + \hat{k}^T \hat{e} . \qquad (7)$$

If $u = u^* + u_s$, then

$$\dot{V}_1 = S(e^{(n)} + \hat{k}^T \hat{e})$$
$$= S[r^{(n)} - f(x, x', \cdots, x^{(n-1)}) - b(u^* + u_s) - d + \hat{k}^T \hat{e}] . \qquad (8)$$

By introducing the perfect control law as Equation (2) into Equation (8), Equation (9) is gotten.

$$\dot{V}_1 = -S(bu_s + d) . \qquad (9)$$

It can be directly verified that if the supervisory control u_s is selected as Equation (5), Equation (9) is always negative. In other words, the system is stable in the sense of Lyapunov.

However, the perfect control law needs to know the functions *f* and *b*. If they are unknown, there is no way of forming the perfect control law. Thus, the CMAC will be employed to the perfect control law in the following two sections.

III. BASIC CONCEPTS OF CMAC

The Cerebellar Model Articulation Controllers (CMAC) firstly proposed by J. S. Albus in the literature [11][12], have several advantages including local generalization [16][17] and rapid learning convergence [18][19]. CMAC seems to be a good candidate for on-line learning control [20] and can be thought of as a learning mechanism that imitates the cerebellum of a human being. The CMAC is often referred to an associative neural network, where only a small subset memory cells mapped by the input vector or so-called state instantaneously determines the output. In fact, CMAC has been regarded as a look-up table neuron computing technique with fast learning convergence.

In the output producing process, a set of association cell indexes $C_{v_k} = [c_1(v_k), c_2(v_k), \cdots, c_j(v_k), \cdots, c_{N_m}(v_k)]^T$ via the *n* dimension input vector $v_k = (x_1, x_2, \cdots, x_n)$ is utilized for address indexes to extract the *L* stored weights from N_m memory cells, which are also called hypercubes in CMAC structure. The constant *L* equals the number of layers in CMAC, and total number of memory cells is N_m. Note that different inputs map into at least one different memory cell, but the association cell indexes mapped by similar input vectors will share memory cells with similar input vectors [17].

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The output producing process can be divided into two parts of mapping in CMAC, which are described as follows:

$$f : S \longrightarrow C \\ g : C \xrightarrow{W} P \tag{10}$$

where S can be n-dimension input space that is quantized into several discrete states according to required resolution. C is a set of association cell indexes, and it contains L's activated elements that equal the layers of CMAC; P is the output space; and $W = [w_1, w_2, \cdots, w_j, \cdots, w_{N_m}]^T$ is the corresponding weight vector in which the mapping information of P is stored. The mapping function f means that each input vector v_k in S maps into association cell indexes, and here are only L's indexes that are activated in C. Through the mapping function g, output P will equal the sum of the weights whose corresponding cell indexes are activated. Its mathematic form can be represented as follows.

$$P_{v_k} = g(v_k) = C_{v_k}^T W = \sum_{j=1}^{N_m} c_j(v_k) w_j \\ c_j(v_k) = \begin{cases} 1; \text{ if } w_j \text{ is activated} \\ 0; \quad\quad \text{others} \end{cases} \tag{11}$$

Only those activated cell indexes $c_j(v_k)$ will be set to be 1 when mapped by input vector, and the others are set to be 0. So here are actually only L's additions in Equation (11), and the actual output P equals the sum of those chosen weights.

The significant property of CMAC is that the learning algorithm changes the output values for the neighboring inputs. Therefore similar inputs lead to similar output even for untrained inputs. This property is called generalization ability [15, 16], which is of great use in CMAC based coding. Moreover, we can control the degree of generalization by changing the size of L. The larger L is, the wider the generalization region is. Thus the generalization property of CMAC can be successfully used for control and image applications, and it also will be applied to learn perfect law of supervisory controls in the next section.

IV. CMAC-BASED LIMITED COMPENSATOR IN SUPERVISORY CONTROL SYSTEMS

In our approach, the CMAC learning mechanism will be employed into the supervisory controller to learn perfect control law and system parameters in supervisory control systems. The block diagram of the CMAC-based limited compensator in supervisory control systems is illustrated in Figure 1. The proposed control laws can be written as Equations (12)-(15). The CMAC variable as Equation (13) is employed to learn the perfect control law u^*, whose weight vector can be updated by supervisory control variable u_s which is described in Equation (15). The CMAC-based compensator is defined as Equation (14), where $\hat{\delta}$ is the estimated bound of compensator. Because the model error will exist in the CMAC, the CMAC-based compensator is proposed to suppress this model error. Finally, the supervisory control can be rationalized for uncertain nonlinear systems, and its Lyapunov stability will be assured in theorem 2.

$$u = u_{CMAC} + u_c + u_s \tag{12}$$

$$u_{CMAC} = C_{v_k}^T W \tag{13}$$

$$u_c = \hat{\delta}[sign(u_s)] = \hat{\delta}[sign(bS)] \text{ for } |u_s| < D_{\max} \tag{14}$$

$$u_s = sat(bS/D_{\max}) \times D_{\max} = \begin{cases} D_{\max} & , for \quad bS/D_{\max} \geq 1 \\ bS & , for \quad -1 < bS/D_{\max} < 1 \\ -D_{\max} & , for \quad bS/D_{\max} \leq -1 \end{cases}$$

$$D_{\max} = sup(\frac{d}{b}) = \frac{d^U}{b_L} \tag{15}$$

Theorem 2:

The control laws of CMAC-based limited compensator in supervisory control systems are described as Equations (12)-(15). If the supervisory control is defined as Equation (15), the CMAC updating law as is considered as Equation (16), the updating law of estimated bound of compensator is considered as Equation (17), and final bound condition (18) is satisfied, then the Lyapunov stability theorems will assured.

$$\dot{W} = r_W u_s C_{v_k} = r_W bS C_{v_k} \text{, for } |u_s| < D_{\max} \tag{16}$$

$$\dot{\hat{\delta}} = r_\delta |u_s| = r_\delta bS[sign(bS)] \text{, for } |u_s| < D_{\max},$$

r_δ =small positive real number. (17)

$$\delta_d > \sup|\delta_W| \tag{18}$$

Proofs:

First, define the Lyapunov function as Equation (19)

$$V = \frac{1}{2}(S^2 + \frac{1}{r_\delta}\tilde{\delta}^2 + \frac{1}{r_W}\tilde{W}^T\tilde{W}). \tag{19}$$

The optimal weight for the CMAC is W^*, the estimated weight vector is defined as W, so its error vector will be $\tilde{W} = W^* - W$. If it exists a model error δ_W, and then the perfect control can be written as $u^* = u_{CMAC} + C_{v_k}^T\tilde{W} + \delta_W$. If the final bound is defined as δ_d and its estimated bound is defined as $\hat{\delta}$, and then bound error can be written as $\tilde{\delta} = \delta_d - \hat{\delta}$. According above definition the proposed controller can be rewritten as follows.

$$u = u_{CMAC} + u_c + u_s = u^* - C_{v_k}^T\tilde{W} - \delta_W + u_c + u_s \tag{20}$$

Now, take Equation (20) into the sliding surface as defined in Equation (7) and we have

$$\dot{S} = e^{(n)} + \hat{k}^T\hat{e} \\ = -b(\frac{d}{b} + u_s + u_c - \delta_W - C_{v_k}^T\tilde{W}) \tag{21}$$

With Equation (21), the time derivative of the Lyapunov function becomes

$$\dot{V} = -bS(u_s + \frac{d}{b}) + [\frac{1}{r_\delta}\dot{\tilde{\delta}}(\delta_d - \hat{\delta}) - bSu_c + bS\delta_W] - (\frac{1}{r_W}\dot{W}^T\tilde{W} - C_{v_k}^T\tilde{W}bS) \tag{22}$$

It is easy to verify that if conditions (14)(16)(17) are satisfied and then Equation (22) becomes Equation (23)

$$\dot{V} = -bS(u_s + \frac{d}{b}) - bS[\delta_d \times sign(bS) - \delta_W]. \tag{23}$$

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If the bound of supervisory control is selected as Equation (15) and $\delta_d > sup|\delta_W|$ is satisfied, then the Lyapunov condition $\dot{V} < 0$ will be assured.

Note that Equation (16) is the updating rule of the CMAC learning mechanism. For the realization of Equation (16), the adjustable constant r_m is set as, where L is the floor number used in the CMAC mechanism. This selection is equivalently to set the learning constant as 1/L for fast learning [18]-[20]. From the definition of saturation function, it can be found that u_s is a bounded version of *bS*. Thus, in our implementation, u_s takes the place of *bS* in Equation (24). Thus the updating rule for the CMAC learning mechanism becomes

$$W_{new} = W_{old} + \frac{1}{L} u_s C_{v_k} . \quad (24)$$

In the above proposed controller as shown in Figure 1, the CMAC control learns the perfect control variable u^*. It can be found that the system function f is no longer required to generate the perfect control variable. However, the estimated bound of compensator will increase with time, because its slope is absolutely positive in Equation (17). Thus, we let the adjust ratio r_δ be a time-decreasing function such that the final bound will converge to a limited region. Under this supposition, theorem 3 is introduced to ensure the convergence of final bound of compensator in the next paragraph. Finally, the CMAC-based limited bound compensator adaptive can be rationalized in supervisory control for uncertain nonlinear systems.

Theorem 3:

If a compensator is considered as Equation (14), the adjust ratio of updating law r_δ is defined as a time decreasing function in Equation (25), and the initial bound equals $\hat{\delta}(0)$,

$$r_\delta(n) = \beta e^{-0.01(n-1)}, \; n\text{=time-step}, \; n \geq 1 \quad (25)$$

then the final bound condition will be assured. In other words, the compensator will be limited in a bounded region.

$$\delta_d = \underset{n\to\infty}{Limit}\, \hat{\delta}(n) \leq \hat{\delta}(0) + 100\beta D_{\max} \quad (26)$$

Proof:

From equation $\dot{\hat{\delta}} = r_\delta(n)|u_s|$ and $r_\delta(n) = \beta e^{-0.01(n-1)}$, we can deduce following equations.

$$\hat{\delta}(n) = \hat{\delta}(n-1) + \beta e^{-0.01(n-1)} |u_s| \quad (27)$$

$$\hat{\delta}(n) = \hat{\delta}(0) + \sum_{i=0}^{n-1} \beta e^{-0.01 i} |u_s| \quad (28)$$

$$\hat{\delta}(n) \leq \hat{\delta}(0) + \beta D_{\max}(1 + \sum_{i=1}^{n-1} e^{-0.01 i}), \; for\; |u_s| \leq D_{\max} \quad (29)$$

$$\hat{\delta}(n) \leq \hat{\delta}(0) + \beta D_{\max}(1 + \sum_{i=1}^{n-1} e^{-0.01}), \; for\; e^{-0.01 i} \leq e^{-0.01}, i \geq 1 \quad (30)$$

$$\delta_d = \underset{n\to\infty}{Limit}\, \hat{\delta}(n) \leq \hat{\delta}(0) + \frac{\beta D_{\max}}{1 - e^{-0.01}} = \hat{\delta}(0) + 100\beta D_{\max},$$
$$for\; e^{-0.01} = 0.99 < 1 \quad (31)$$

Thus, the final bound condition (26) will be assured, in other words, the compensator will be limited in a bounded region.

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V. Simulations and Conclusions

An inverted pendulum system as used in [13] is employed to illustrate the effectiveness of the proposed approaches. The dynamics of this nonlinear system is

$$\dot{x}_1 = x_2$$
$$\dot{x}_2 = f + bu + d \,;\; y = x_1 \,;$$
$$f = \frac{g \sin x_1 - (m l x_2^2 \sin x_1 \cos x_1)/(m_c + m)}{l(4/3 - m\cos^2 x_1 / m_c + m)}$$
$$b = \frac{\cos x_1 / (m_c + m)}{l(4/3 - \cos^2 x_1 / m_c + m)}, \quad (32)$$

where x_1 is the angle of the pole with the range of initial angles in 0~$\pm$ 0.2(*rad*), x_2 is the angular velocity of the pole, g is the gravity (9.8m/s^2), m_c is the mass of the cart (1.0*kg*), m is the mass of the pole (0.1*kg*), u is the force applied to the cart, d is the external disturbance ($-5Nt \leq d \leq 5Nt$), and the length of the pole l is 0.5*m*. Let the reference signal be $r(t)$ and the tracking error be $e(t) = r(t) - y(t)$. The error derivative is simply calculated as $\dot{e}(t) = [e(k) - e(k-1)]/t_s$, where t_s is the sampling time. The reference signal is $r(t) = \frac{\pi}{10}[\sin(t) + 0.3\sin(3t)]$ (*rad*), the initial value of $y(0)$ is 0.2(*rad*) and the external disturbance is a square wave with its amplitude being 5(*Nt*). From the above conditions and Equation (32), the range of the parameter b is 1.38<b<1.48. According to Equation (15) ($D_{\max} = \sup\left|\frac{d}{b}\right|$), the robust control bound $D_{\max}$ is set to be 4.

Now, the proposed controller is employed. The control performances are shown in Figure 2 with initial estimated bound $\hat{\delta}(0) = 4$ and in Figure 3 with initial estimated bound $\hat{\delta}(0) = 0.4$. The part (a) shows the reference signal r and the output y, the part (b) shows the control variable u and the external disturbance d, the part (c) shows cthe supervisory control, the part (d) shows the CMAC control variable, the part (e) shows the compensator output, and the part (f) shows the estimated bound of compensator.

From the simulation results, it can be found that although the reference signal is time-varying and with external disturbances, the output can follow reference signal very well with the proposed control structure. In fact, in our study, other values of initial bound from 0.4 to 4 were also considered, the final bound of compensator will also converge to a bounded region, and their performances and RMSEs are almost the same. Thus, it can be concluded that the CMAC-based limited bound compensator indeed can learn the perfect control law required in a supervisory controller for uncertain nonlinear systems, and the proposed controller can easily be realized for any practical systems even if the system function is uncertain..

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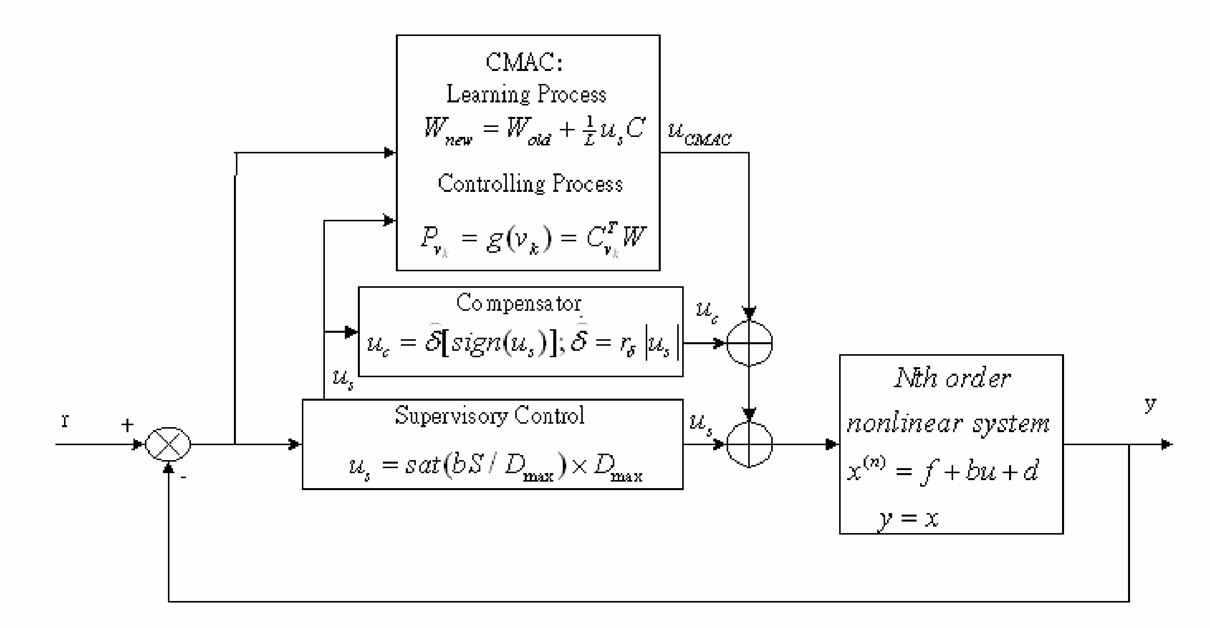

Figure 1. The block diagram of the CMAC-based limited compensator in supervisory control systems

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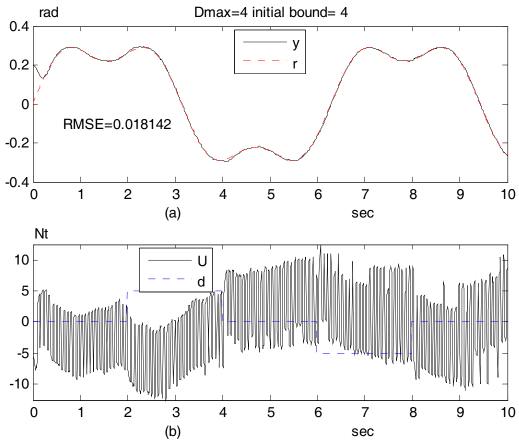

Figure 2. The performance of CMAC-based limited bound compensator in supervisory control systems with initial estimated bound $\hat{\delta}(0)=4$. (a) the reference signal r and the output y, (b) the control variable u and the external disturbance d.

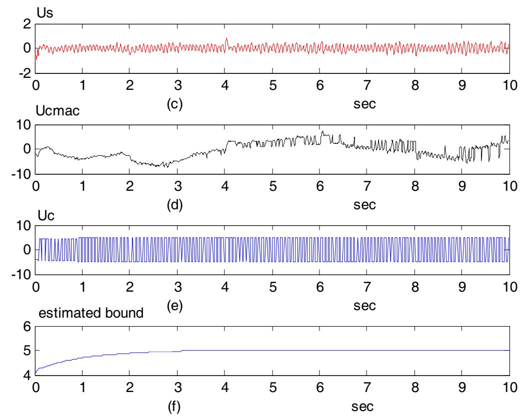

Figure 2. (c) the supervisory control ,(d) the CMAC control variable, (e) the compensator output, (f) the estimated bound of compensator with initial estimated bound $\hat{\delta}(0)=4$.

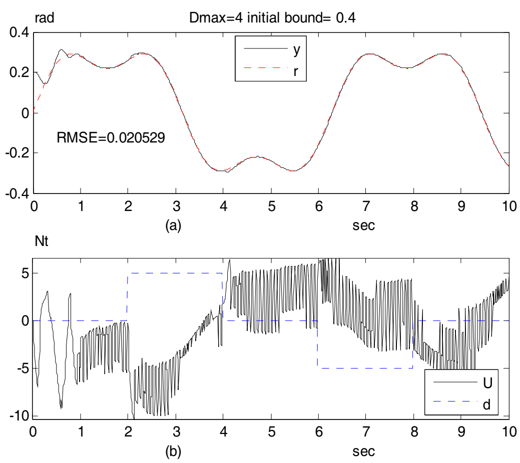

Figure 3. The performance of CMAC-based limited bound compensator in supervisory control systems with initial estimated bound $\hat{\delta}(0)=0.4$. (a) the reference signal r and the output y, (b) the control variable u and the external disturbance d.

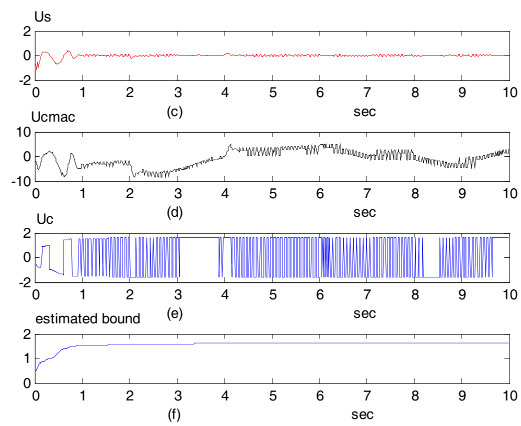

Figure 3. (c) the supervisory control ,(d) the CMAC control variable, (e) the compensator output, (f) the estimated bound of compensator with initial estimated bound $\hat{\delta}(0)=0.4$.

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