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Use of Numeric-to-Symbolic Converters for Adaptation in Control Systems

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ABSTRACT

A new control scheme is proposed in this paper which can cope with varying environment as results of load disturbances, changes of plant dynamics, and failures of components. The objective of this paper is to blend numeric-to-symbolic conversion techniques with linear conventional controllers so as to adapt to the varying environment of the system.

The control scheme is based on the parametrization of stabilizing controllers, which is called Kucera/Yula parametrization. The parametrization has been extended to the class of systems which contain numeric-to-symbolic converters. It is shown how the numeric-to-symbolic converters can be blended with the linear controllers.

1. Introduction

A new control scheme is proposed in this paper which can cope with varying environment as results of load disturbances, changes of plant dynamics, and failures of components. Many adaptive control methods have been applied to the systems with varying environment. There are several problems in use of adaptive control techniques; for examples, burst behavior from wrong assumptions [1], lack of proof in convergence of algorithms [2], chaotic phenomena from nonlinearity [3]. Another relatively new idea for adaptation to varying environment is to give much attention on event-driven problems in control systems [4]. In most of actual plants, the change of plant parameters occurs only at discrete points in time in response to the failure of the components. The disturbance comes into the system at the time when the particular event occurs. If we know how the failures have effects on the plant dynamics; moreover, we can detect the failures or the occurrence of the event, we can tune the controller parameters so as to keep the performance, or to suppress the deterioration. Therefore, incorporation of human intelligence into control systems has been considered, which is classified into heuristic control schemes. Fuzzy theory and neural networks can be used for such a purpose, and implemented easily in digital computers [5], [6]. While many applications of these heuristic approaches have been realized, linear controllers still keep important roles in industrial processes. In most of actual situations, changes of environment occur in the systems which are controlled by the linear controllers. So, it is desirable to blend heuristic decision techniques with linear controllers.

The objective of this paper is to blend numeric-to-symbolic conversion techniques with linear controllers so as to adapt to the varying environment of the systems. The task taken up in this paper is to conveniently parametrize the class of all stabilizing controllers. The parametrization is in terms of an arbitrary proper stable transfer function, and has been extended to the class of systems which contain numeric-to-symbolic converters. A neural network with back propagation training rule is used as the numeric-to-symbolic converter. The numeric-to symbolic converter is trained in closed-loop with prior knowledge about varying environment. It is shown how the numeric-to-symbolic converters can be blended with the linear controllers and the proposed control scheme improves the adaptability of the hybrid control systems. A simulation example is given to illustrate the efficiency of the proposed control scheme.

2. Class of all stabilizing controllers

In this section, background theory is organized. Given a linear plant with nominal state space description

$$\dot{x} = Ax + Bu, \quad y = Cx \tag{1}$$

and transfer function

$$P(s) = C(sI-A)^{-1}B \;\text{<->}\; \left[\begin{array}{c|c} A & B \\ \hline C & 0 \end{array}\right] \tag{2}$$

We assume that $K(s)$ is a stabilizing controller characterized in terms of F, H as

$$K(s) \;\text{<->}\; \left[\begin{array}{c|c} \bar{A} & H \\ \hline -F & 0 \end{array}\right] \tag{3}$$

where

$$\bar{A} = A + BF + HC \tag{4}$$

and where both of $A+BF$ and $A+HC$ have to be Hurwitz. It is clear that $K(s)$ can be designed as an LQG controller. The class of all stabilizing controllers for $P(s)$ has the form of Fig.1 [7], which is parametrized in $Q(s) \in RH\infty$ (Kucera/Yula Parametrization). The $J(s)$ is defined as follows:

$$J(s) \;\text{<->}\; \left[\begin{array}{c|cc} \bar{A} & H & -B \\ \hline -F & 0 & I \\ C & I & 0 \end{array}\right] \tag{5}$$

If $Q(s)=0$, then the controller for $P(s)$ is $J_{11}(s)$. When there are some time-varying disturbances or time-varying perturbations of the plant dynamics, we can utilize free parameters $Q(s)$ of the augmented controller to reduce the effects on the performance. Tay and Moore [8] proposed a useful method in which $Q(s)$ is adaptively tuned to reject the time-varying disturbances. However, in the case of perturbations of plant dynamics, we cannot ensure any longer the stability of the control system. Obinata and Moore [9] gives a parametrization for the class of all stabilizing controllers for two or more plant dynamics. Optimal tuning of free parameters is difficult in the case. In this paper, we take another approach for tuning $Q(s)$, which is explored in subsequent sections.

3. Classification of events using neural network in closed-loop and adaptation to the change of dynamics.

We can find out a lot of event-driven problems in actual control systems [4],[10]. In most of actual plants, the change of plant parameters occurs in response to the failure of the components. The disturbance comes into the system at the time when the particular event occurs. We may know the pattern of the changes or the characteristics of the disturbances corresponding to the event. In adaptive control scheme, the change of the dynamics has to be identified with accuracy. If we have prior knowledge about the pattern of the change, it is a relatively easy task to classify the event which causes the corresponding change. This is the point of this method which differs from traditional adaptive control scheme.

In this section, a neural network is used to classify numeric data and assign symbols to various classes. After introducing the idea of using the neural network as a numeric-to-symbolic converter, its use in closed-loop system is discussed. Assume that we know the several dynamics of the plant P_{00}, P_{01}, ... which are determined and driven by the discrete events, and the controller K for nominal plant P is designed. Time histories of plant inputs and outputs corresponding to each dynamics can be obtained in the closed-loop system with the nominal controller, shown in Fig.2. The input of the neural network is set equal to the state of the plant and the input of the control system. The neural network considered here contains a single hidden layer between the input and the output layers, as illustrated in Fig.3 for the case of four nodes at input and hidden level, and two nodes at output level. The neural network is trained by back-propagation to classify the plant dynamics with the prior knowledge of the dynamics. The desired responses for the neural network are binary valued symbols which represent each dynamics. Therefore, the neural network in our method is used as a numeric-to-symbolic converter. After the training stage, we set the neural network in the closed-loop for detecting the change of plant dynamics. If the plant keeps the nominal dynamics, the output of the neural network indicates the binary valued symbol. When the change of the plant dynamics occurs, the corresponding symbol will be obtained as an output of the neural network. We can tune or change the controller based on the symbols given by the neural network. However, a sudden change of the controller is undesirable; moreover, it is difficult to guarantee the performance during the tuning stage. We will propose the method that the tuning part of the controller is combined to the fixed main controller as an additional loop. The structure comes from the parametrization of all stabilizing controllers, which is already mentioned in section 2. So, the controller which represents the class of all stabilizing controllers: Fig.1, is reorganized with the neural network as in Fig.4. The output of the neural network works as a switch which selects suitable tuning part for the changed dynamics. If the selected tuning part is a proper stable system, the stability of the closed-loop system is guaranteed [8].

4. Simulation results

In this section, an example of how numeric-to-symbolic conversion can be done via the neural network is given. Consider the following simple SISO system with the transfer function:

$$P_{00}(s) = k_0/\{s(1+T_0 s)\}, \quad k_0 = 1, \quad T_0 = 0.1$$

$$\Longleftrightarrow \left[\begin{array}{cc|c} 0 & 1 & 0 \\ 0 & -10 & 10 \\ \hline 1 & 0 & 0 \end{array}\right] \tag{6}$$

The changes of the plant Dynamics are taken into considerations as follows:

$$P_{ij}(s) = k_i/\{s(1+T_j s)\}, \quad i=0,1 \quad j=0,1 \tag{7}$$

where the necessary information on k_i, T_j is given in Table 1 to specify the classification of the plant dynamics. At first step, an LQG controller is designed for the nominal plant. Find a controller to minimize

$$J = \int_0^\infty (q \cdot y^2 + u^2)\, dt \tag{8}$$

where y is output and u is input of the plant, and q is the weight for the output. We set $q = 30.0$. The optimal control has the form

$$u = Fx = [f_1, f_2]x \tag{9}$$

A Kalman filter is constructed to estimate the state vector as follows:

$$\dot{\hat{x}} = A\hat{x} + Bu + H(y - C\hat{x}) \tag{10}$$

Filter gain H should be determined for loop transfer recovery [11]. From designed $F = [-3.162, -0.2777]$ and $H = [-7.321, -26.79]'$, $J(s)$ is obtained according to (5) as follows:

$$J(s) \Longleftrightarrow \left[\begin{array}{cc|cc} -7.321 & 1 & 7.321 & 0 \\ -58.42 & -12.78 & 26.79 & 10 \\ \hline -3.162 & -0.2777 & 0 & 1 \\ -1 & 0 & 1 & 0 \end{array}\right] \tag{11}$$

Fig.5 shows the simulation result for initial state x(0) = [1,0] when Q(s) = 0. The responses for the changed dynamics of the plant are also shown in Fig.5, Fig.6 and Fig.7 with the nominal controller: the case of Q(s) = 0. It is clear that the dampings for the changed dynamics are not enough in comparison with the nominal case. We can tune Q(s) for improving the dampings using H_2 or H_∞ optimization techniques under an appropriate assumptions. The optimization problem is not main problem of this paper; therefore, the technique is not explored further here. For the classification of the plant dynamics, we set inputs and desired output of the neural network: the inputs of the neural network are the output y, the derivative y of the plant, the reference input r, and the derivative r and the outputs of the neural network are the binary valued symbols corresponding to the plant dynamics (See Table 1). Thus, the neural network has four inputs and two outputs. After several trials, we recognized that ten hidden units of the neural network are suitable to this classification. The task of the classification for the neural network is not so easy because there are a few parameters in the training stage whose meanings are not clear to the learning with back-propagation. We tried several parameters, but we could not realized the perfect classification. However, the trained neural network gives high reliability. The time series for the inputs of the neural network are checked during a short time interval, then the numeric-to-symbolic conversion is done by the neural network if the checked time series are classified as one plant dynamics with the majority. We can use the neural network with this modification for classifying the plant dynamics with high accuracy. A typical example is shown in Fig.8 in the case of the change from P_{00} to P_{01}. Fig.9 shows the result in the same condition with no tuning of the controller. Note that the tuning of Q(s) do good on recovering the gain in the response. We can see the similar results in Fig.10 and Fig.11. In this case, longer duration of time was needed for detecting the change of the plant dynamics.

5.Conclusion

A new control scheme has been proposed for adapting to the varying environment of systems in this paper. The control scheme is based on the parametrization of all stabilizing controllers. The parametrization has been extended to the case of systems which contain numeric-to-symbolic converters. The numeric-to-symbolic converter detects the change of the plant dynamics and selects an appropriate tuning part of the controller. It is shown that the control scheme of this paper is a relatively easy task in comparison with traditional adaptive control scheme.

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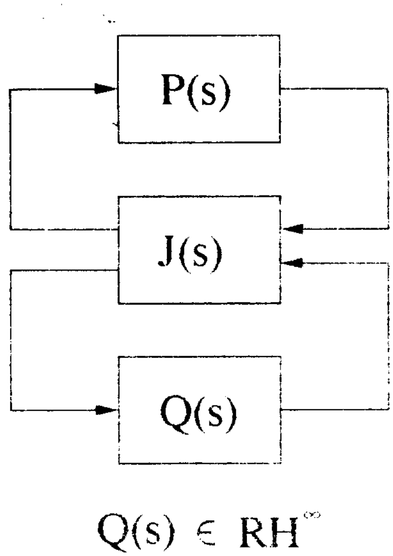
Plant	P_{00}	P_{01}	P_{10}	P_{11}
Plant dynamics	$\frac{1}{s(1+0.1s)}$	$\frac{0.5}{s(1+0.1s)}$	$\frac{1}{s(1+0.4s)}$	$\frac{0.5}{s(1+0.4s)}$
Assigned symbols	(0,0)	(0,1)	(1,0)	(1,1)

Table 1 Plant dynamics and numeric-to-symbolic conversion specifications.



$Q(s) \in RH^{\infty}$

Fig.1 Class of all stabilizing controllers.

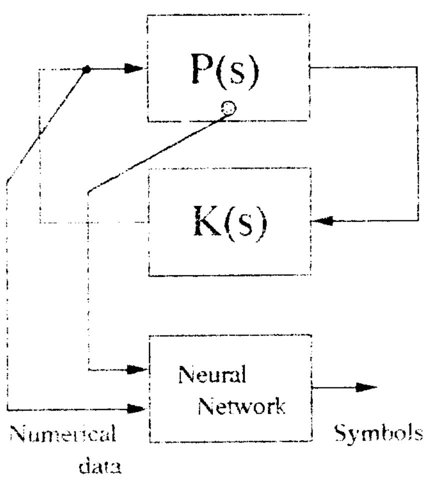


Fig.2 Classification of events using neural network in closed-loop.

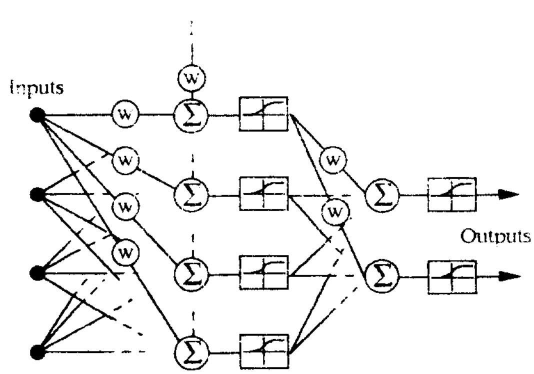


Fig.3 Three-layer neural network.

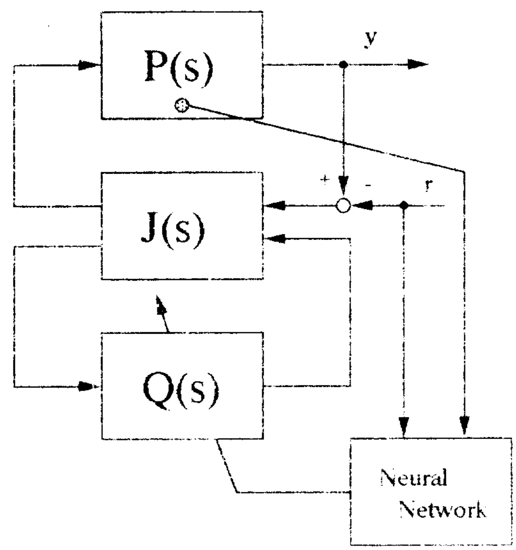


Fig.4 Adaptive scheme using neural network.

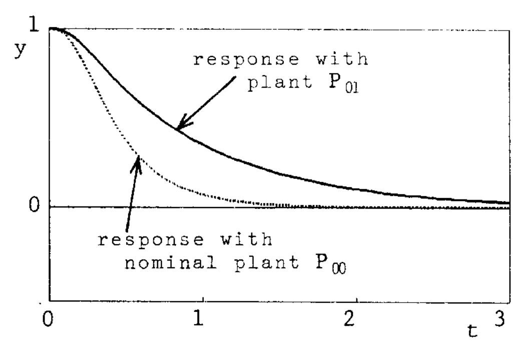


Fig.5 Responses of the control system to initial state (P_{00}, P_{01})

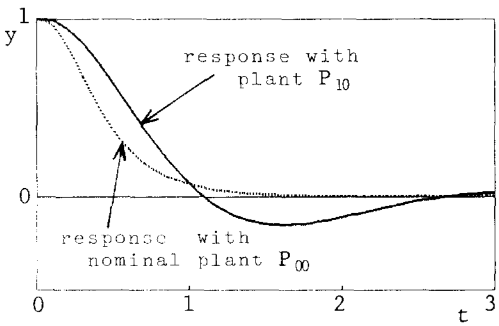


Fig.6 Responses of the control system to initial state (P_{00}, P_{10})

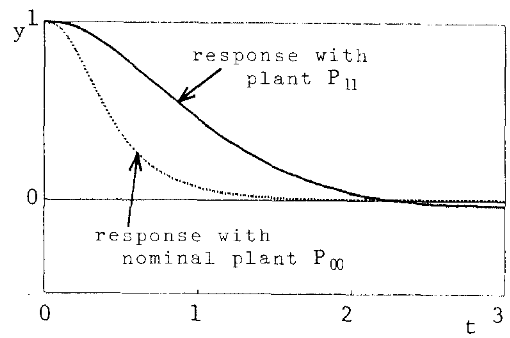


Fig.7 Responses of the control system to initial state (P_{00}, P_{11})

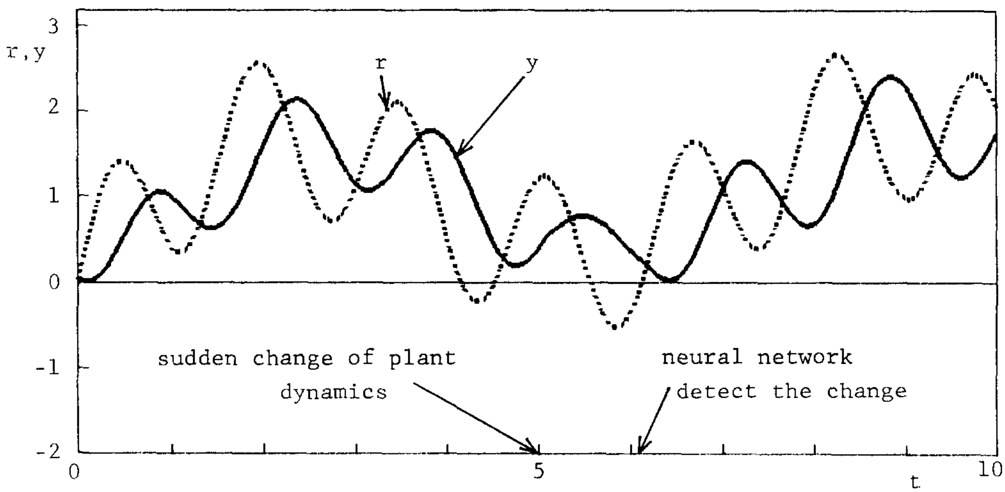


Fig.8 Reference input and plant output: change from P_{00} to P_{01} with adaptive scheme

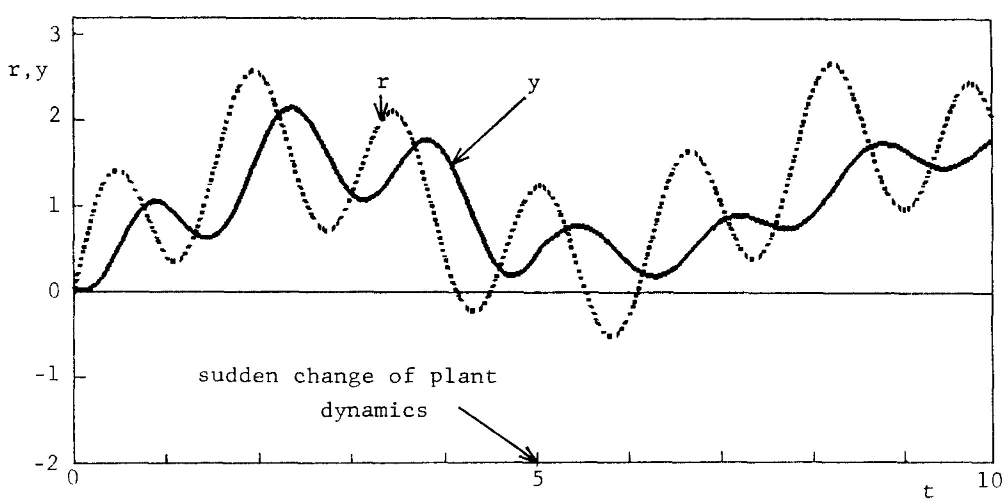


Fig.9 Reference input and plant output: change from P_{00} to P_{01} without adaptive scheme

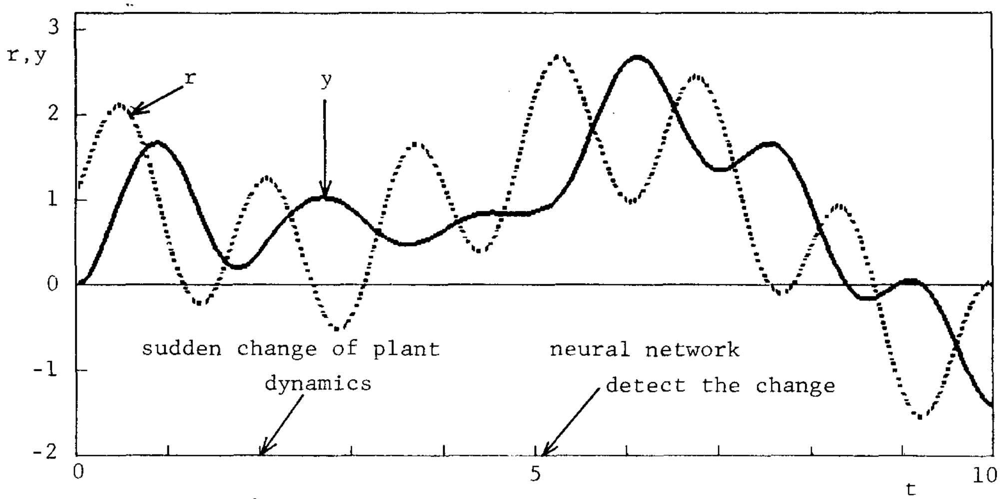


Fig.10 Reference input and plant output: change from P_{00} to P_{11} with adaptive scheme

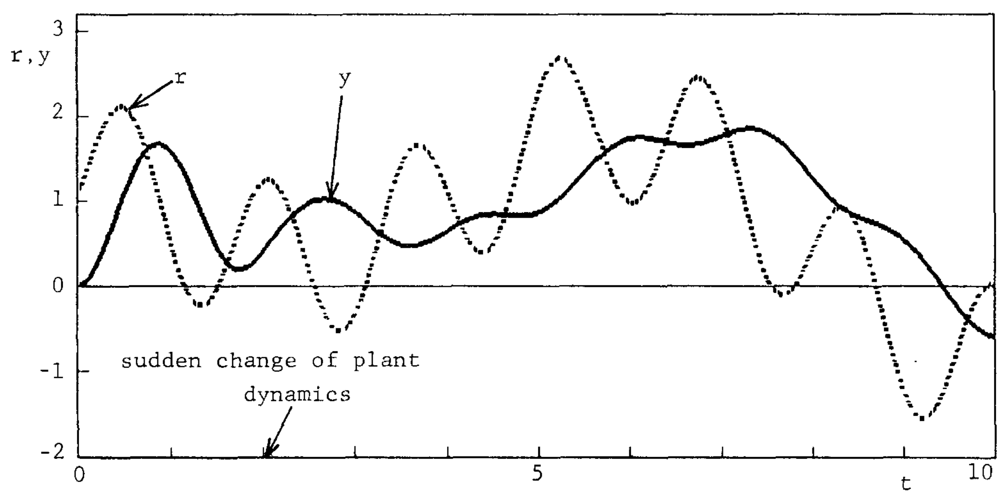


Fig.11 Reference input and plant output: change from P_{00} to P_{11} without adaptive scheme