A Fuzzy Supervisor for Proportional-Plus-Derivative Controllers

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Abstract—The design of a fuzzy logic supervisor for systems controlled by PD controllers is carried out in this paper. The objective of the fuzzy supervisor is to modify the controller parameters while the system responds is in its transient state. The advantage of the fuzzy supervisor is its ability to maintain a desired system response when uncertainties are introduced in the system. Simulation results are presented, comparing the results of the fuzzy supervised system with conventionally controlled systems.

I. Introduction

Conventional controllers, such as proportional-plus-integral-plus-derivative (PID) and proportional-plus-derivative (PD) controllers, have been successfully used in industry. However, the controller design does not take into account uncertainties that may change the transfer function of the system. As the operating environment changes, the PD and PID control parameters must be manually adjusted to achieve a desired response. An alternative is to replace the existing controller with a self-organizing or adaptive fuzzy logic controller (FLC) [1]. These techniques involve replacing the conventional controller with the fuzzy controller. A second alternative, one presented in this paper, is to supervise the existing PD controller with a fuzzy system to obtain the desired response. This fuzzy supervisor operates in a manner similar to that of the fuzzy logic controller and adds a higher level of control to the existing system. The resulting improvements in the system response are accomplished by making online adjustments to the control parameters [2,3].

In this paper, the performance of PD controlled systems is shown to improve with the addition of the fuzzy logic supervisor (FLS). The PD controllers are designed using classical design methods. It will be shown (through simulation) that a gradual increase in the proportional gain ($K_P$) of the controller, as the system error decreases, results in an improved system response. The derivative gain ($K_D$) is determined by multiplying the new proportional gain by the ratio of the original parameters ($K_D/K_P$). Section 2 discusses the basics of fuzzy logic controllers. Section 3 discusses the design of the fuzzy supervisor, and Section 4 provides simulation results.

II. Fuzzy Logic Control

Because the basic operation of the fuzzy supervisor is similar to that of the FLC, this section discusses some of the basic concepts of the fuzzy logic controller (figure 1). Differences between the FLC and the fuzzy supervisor will be addressed in the next section.

A. Fuzzification

The FLC has three main components: fuzzification, a knowledge base, and defuzzification. Fuzzification converts a crisp input signal into a fuzzified signal identified by its level of membership into a fuzzy set. The knowledge base is a collection of linguistic statements (rules) relating the input conditions to the fuzzified output. Finally, the process of defuzzification determines the controller output and converts it into a crisp controlling signal.

Figure 1: Fuzzy logic controller.

The process of fuzzification receives a crisp input signal, normalizes it and classifies it into membership functions. A grade of membership (a value between zero and one) which measures the compatibility of the signal to the membership function, is assigned to the signal. Each membership function is identified by a linguistic variable like small, large, and very large. The shapes of the membership functions are typically triangular or exponential. In this paper triangular membership functions are used. Figures 2(a) and 2(b) show triangular membership functions, for the error and change in error, with fuzzy labels NB (negative big), NM (negative medium), NS (negative small), ZO (zero), PS (positive small), PM (positive medium), and PB (positive big).
(positive big) for error and change in error.

Figure 2: Triangular membership functions.

In the case of the triangular functions shown in figure 2(a), the normalized error signal (e) has membership in both the ZO and PS functions, while figure 2(b) shows the change in error signal with membership in both the NS and ZO functions. The values of points a and b represent the grade of membership of the error in the ZO and PS functions, and the values of points c and d represent the grade of membership of the change in error in the NS and ZO functions. The sum of a and b, and the sum of c and d, will always be equal to one for triangular membership functions.

B. The knowledge base

The knowledge base for the fuzzy controller is a collection of linguistic statements (rules) relating the input signals to an output condition. One method of storing the knowledge base is the use of the Macvicar-Whelan control matrix [4] (figure 3). This matrix is designed so that if the desired output is realized with zero change in error then the output remains constant. However, if the output is not the desired response, then the rule matrix produces an output signal, based on human knowledge of the operating system. Each element of the matrix describes a rule which is given by

\[ y(t) = \frac{a \cdot c \cdot PS + a \cdot d \cdot ZO + b \cdot c \cdot NS + b \cdot d \cdot ZO}{a \cdot c + a \cdot d + b \cdot c + b \cdot d} \]  

where a and b, represent the membership values for the error, c and d represent the membership values for the change in error, and the terms NS, ZO, and PS are the peak values of the output membership functions. It should be noted that the denominator in (1) will be one when the triangular functions are symmetric.

C. Defuzzification

Choosing triangular membership functions, for the input signals, ensures that a maximum of four rules apply for the error shown in figure 2(a) and the change in error shown in figure 2(b). To determine the output value, a weighted average of the active rules is used. This method is illustrated in figure 4 with the output realized by

Figure 3: Macvicar-Whelan fuzzy rule matrix.

III. The Fuzzy Supervisor

Conventional PD and PID control is widely used in many industrial processes. Because of parameter variations and other uncertainties introduced in the systems, the transfer function of the plant may change and the desired response may no longer be realized with the existing controller. As a result, the controller may have to be manually tuned to obtain the desired response. The addition of a higher level of control, through a fuzzy logic supervisor,
can enhance the system performance under normal operating conditions and when uncertainties are introduced. A general block diagram of a fuzzy supervised system is shown in figure 5. System control is still accomplished by the conventional controller but the gain values $K_P$ and $K_D$ are now controlled by the FLS. Figure 6 shows the general structure of the fuzzy logic supervisor. Inputs to the supervisor are the error and change in error of the system response. The outputs ($\Delta K_P$ and $\Delta K_D$) are the incremental changes to be made to the existing parameters.

**Figure 5:** PD control with fuzzy supervisor.

**Figure 6:** Fuzzy supervisor structure.

While the basic operation of the fuzzy supervisor is similar to that of an FLC, it is not designed to provide the total controlling action. Instead, the FLS is designed to provide incremental changes based on how a human would operate the system.

A. *Supervisor control matrix*

It has been shown, for conventional PD fuzzy controllers [5], that a gradual increase in the proportional gain as system error decreases reduces the overshoot of the system. This concept is used for the design of fuzzy supervisor. The development of the supervisor control matrix is based on the observation of a typical step response shown in figure 7.

**Figure 7:** Typical step response.

The step response (figure 7) is divided into four general regions, each determined by the sign of the error and change in error. The regions are:

- **Region 1:** Positive error, negative change in error
- **Region 2:** Negative error, negative change in error
- **Region 3:** Negative error, positive change in error
- **Region 4:** Positive error, positive change in error

A fifth region (the zero region) is used when both the error and change in error are near zero and is not dependent on the sign of the signals.

Initially the error is one (PB) and the change in error is zero (ZO). This condition is identified by the linguistic statement

\[ \text{if } e(t) \text{ is PB and } de(t) \text{ is ZO, then } y(t) \text{ is ZO,} \]

which states that the supervisor output is zero and no changes are made to the existing control parameters. As the error begins to decrease toward zero and the change in error increases in a negative direction (region 1), the supervisor output is gradually increased from zero towards a maximum of one. Using the supervisor output ($y(t)$), the incremental changes are calculated as

\[ \Delta K_P = y(t) \cdot K_P \]
\[ \Delta K_D = y(t) \cdot K_D \]

This ensures that the original ratio $\frac{K_D}{K_P}$ is maintained.

When the system error becomes negative (region 2), the system needs to be slowed down to reduce the overshoot. This is accomplished by decreasing the value of the control parameters. The supervisor output in this region is a negative value. As the overshoot reaches a peak value, the change in error of the system becomes a positive value (region 3). Once again the the controller gains are increased in value until the response enters region 4. In region 4, the error is again positive, but the signal is moving away from the desired steady-state value. To reduce the overshoot, the parameter values are gradually...
decreased until the response is moving toward the desired response. The process continues until both the error and change in error values are classified in the zero membership region. At this point both $\Delta K_P$ and $\Delta K_D$ are maximized.

The resultant supervisor control matrix is shown in Figure 8. A total of nine membership functions for both input and output signals are used. The membership functions are described as NL (negative large), NB (negative big), NM (negative medium), NS (negative small), ZO (zero), PS (positive small), PM (positive medium), PB (positive big) and PL (positive large).

![Figure 8: Fuzzy supervisor rule matrix.](image)

IV. Simulation Results

To test the effects of the fuzzy supervisor, simulation was performed on two different systems, a servo motor system (type-1) and a single link flexible arm (type-0 system).

A. Servo Motor System

The first system tested was a servo motor system with the transfer function given by $G(s) = \frac{218}{s^2 + 2.14}$. A PD controller was first designed for $\zeta = 1$ and $t = 0.1$ seconds. The gains were found as $K_P = 7.34$ and $K_D = 0.36$. These control parameters were also supplied to the fuzzy supervisor. Figure 9 shows a comparison of the two systems, showing that the fuzzy supervisor actually improves the system response.

![Figure 9: Response of servo motor with classical PD and supervised PD control.](image)

The next step was to simulate an uncertainty introduced into the system by changing the transfer function of the servo system to $G(s) = \frac{100}{s^2 + 2.14}$. The PD controller parameters were kept the same. Figure 10 shows the simulation results of the new system. The dotted line is the system response without the FLS and the solid line is the response of the same system with the fuzzy supervisor. The results show that the supervised system response meets the original system requirements.

![Figure 10: Response of altered servo motor system with classical PD and supervised PD control.](image)

B. Flexible Arm

A type-0 system was used as a second example. The system is a single link flexible arm with the transfer function given by $G(s) = \frac{43.75}{s^2 + 43.75}$. The initial design parameters are $K_P = 100$ and $K_D = 2$. Since the system is type-0 the system has a steady-state error given by $e_{ss} = \frac{1}{100}$. Figure 11 shows the step response to the system with both the conventional
PD controller and the supervised system. The results show a small reduction in the steady state error as well as elimination of the overshoot.

An uncertainty in the system is simulated by changing the transfer function of the flexible arm to \( G(s) = \frac{1}{s^2 + 37.5} \). Again the controller parameters were kept the same. The supervised system once again is shown to improve the response of the system under abnormal conditions, as shown in figure 12.

Figure 11: Response of degraded system with PD control and supervised PD control.

Figure 12: Response of degraded system with PD control and supervised PD control.

V. Conclusions

The application of a fuzzy supervisor to systems controlled by classical PD controllers is studied in this paper. It is shown that the addition of a fuzzy logic supervisor improves the response of a PD controlled system under normal operating conditions and when uncertainties are introduced into the system. The design of the fuzzy supervisor is based on human observation of a typical step response. Gradual increases in the controller gains, as the system response approaches zero error, provide improved system operation. In summary, the fuzzy supervised controller improves system response by making on-line modifications to the original control parameters.

References