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Thomas Hessburg and Masayoshi Tomizuka

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Abstract

A fuzzy rule-based controller is applied to lateral guidance of a vehicle for an automated highway system. The fuzzy rules, based on human drivers' experiences, are developed to track the center of a lane in the presence of external disturbances and over a range of vehicle operating conditions. In the case of a severe road curvature, rules are developed to provide feedforward steering action, utilizing preview information regarding the characteristics of the upcoming curve. A nonlinear model is used to simulate the performance of the fuzzy rule based controller for a variety of scenarios.

1 Introduction

This paper proposes a fuzzy rule-based controller for automotive vehicle guidance. The objective of lateral guidance is to control a vehicle tracking the center of a lane, while in the presence of disturbances such as wind gusts, and over a range of operating conditions such as vehicle mass, longitudinal velocity, and traction characteristics between the tires and the surface of the road.

Fuzzy rule-based control stems from fuzzy set theory proposed by Zadeh [1]. Control based on a fuzzy rule base is said to exploit the allowable tolerances of the system. Motivation for a fuzzy rule-based controller to steer a vehicle arises from its capability to deal with steering decisions by "IF, THEN" rules, similar to the method of human reasoning used when humans operate a vehicle. Also, the flexibility of a fuzzy rule-based controller allows for a variety of system inputs manipulated in an efficient manner. Rules based on the human decision-making process can be complemented with rules based on control theoretic techniques intended to enhance performance and robustness characteristics of the closed loop system. In addition, fuzzy rules provide an effective means of handling the issue of using measurements and estimates which may be imprecise.

Some background information of the system may be useful. The plant is an automobile which follows a predetermined path of discrete magnetic markers which make up the reference / sensing system [2]. The controlled output is the front wheel steering angle command. For this investigation, the controller is capable of acquiring measurements or estimations of lateral error, cornering stiffness, and longitudinal velocity. Finally, as a capability of the discrete magnetic marker system to transmit binary coded information, the controller has access to preview information with respect to the location, direction, and severity of upcoming curves in the roadway.

The work presented in this paper focuses attention on achieving good tracking for a variety of roadway curves over a range of cornering stiffness and longitudinal speed of the vehicle. The fuzzy rule based controller is broken into four types of rules: a) feedback, b) parameter robustness, c) integral action, and d) feedforward.

The rules which make up the basic feedback control structure are the "Feedback Rules". These rules use as linguistic input variables LE (Lateral Error) and CLE (Change in Lateral Error). These variables are used in premises for rules based on "human type" decisions on choosing AD, the linguistic variable for front wheel steering angle command to the vehicle.

The “Parameter Robustness Rules” use V (longitudinal Velocity) and CS (Cornering Stiffness) to allow the closed loop system to have satisfactory performance over a wide range of vehicle speeds and road conditions. Note that the mass of the vehicle is not considered. Simulations show that variations in mass have little effect on the response of the closed loop system.

The “Integral Action Rules” consider situations where an integral terrn would be desirable to eliminate some steady-state error. For instance, suppose the path of the roadway slightly deviates from a perfectly straight line to a slowly varying, gradual curve. Preview information only informs the controller of severe curvature sections, as encoding all levels of curvature would result in an inefficient use of the fuzzy rule-base and encoding data base. Also, consider an external disturbance in the form of a side-wind. The “Integral Action Rules” use LE and AA (actual steering angle) over a past finite number of magnetic markers to first determine if the roadway has any unforeseen curvature or perhaps low frequency wind gust disturbance, and if so, how severe is the curvature or wind gust. The values of LE and AA determine the weight of integral action rules, as will be discussed later.

Roland and Sheridan suggest that preview information of an on-coming curve is vital for human drivers [3]. In addition, McRuer [4] proposed a model for lane-following by human drivers which consists of two parts: 1) the pursuit (open loop) block and 2) the compensatory (closed loop) block. Furthermore, experiments conducted by Donges [5] suggest that human drivers anticipate curvature changes and initiate front-wheel steering before the curve begins. Godthelp [6] considered this result when he proposed a method of implementing front-wheel steering action for constant curvatures. The results of these references are used to develop the “Feedforward Rules”, which consider how values for the linguistic variables V and CRV (curvature from preview information; if p is the radius of curvature, then the curvature, c, is $1/\rho$) should influence AD, in coordination with the “Feedback Rules”. The “Feedforward Rules” are only active if the controller is warned by preview information of an upcoming curve. Preview control techniques applied to vehicle guidance based on control theory have been developed in [7] and [8].

2 Basics of Fuzzy Control Algorithms

Fuzzy set theory has a variety of applications, among which is system control. Fuzzy sets can be thought of as a generalization of a crisp set. An element either belongs to or does not belong to a crisp set. For instance, define the crisp set $S \equiv \{x: 0 \le x \le 2\}$. The element $x_1 = 1$ belongs to S, but $x_2 = 5$ does not. In contrast, a fuzzy set considers elements which have a certain degree of membership to a particular fuzzy set. For example, consider a fuzzy subset, $\widetilde{A}$, called “warm temperature", and an element, $x = 65°F$, among the set of all possible temperatures, T. A membership function, $\mu_{\tilde{A}}(x)$, is a mapping $\mu: T \rightarrow [0,1]$, where 1 implies full membership to the fuzzy subset and 0 implies no membership. Therefore, $\mu_{\tilde{A}}(x)$ is the degree which x belongs to $\tilde{A}$.

As with crisp subsets, set operations such as unions and intersections can be performed on fuzzy subsets. Since fuzzy subsets are characterized by membership functions, so are the fuzzy set operations. Although many consistent methods are available for these two operations, the min-max model, proposed by Zadeh is the most common. For example, if $\tilde{A}$ and $\tilde{B}$ are two fuzzy subsets, the degree to which "x" belongs to $\tilde{A}$ AND $\tilde{B}$ is $\min\{\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(x)\}$, while the degree to which "x" belongs to $\tilde{A}$ OR $\tilde{B}$ is $\max\{\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(x)\}$. Refer to [9] for more details of these fuzzy set operations.

Fuzzy set operations are the mathematical tool required to evaluate "IF, THEN" rules in a fuzzy rule-based controller. Several methods are available to develop these rules such as observation of human operators of the given system, fuzzy modeling, and our choice for this investigation, rule development based on experts' experiences and knowledge. Our rules are developed from information from a survey passed out among vehicle operators, heuristic and engineering judgement, and dynamic considerations.

The advantage of fuzzy rule-based control is its ability to develop rules which make intuitive sense and can be expressed in linguistic terms. Using vehicle guidance as a working example, consider two rules[1].

1) IF LE is PB and CLE is PB OR PS THEN AD is NB
2) IF LE is PB and CLE is NIL THEN AD is NM

If one imagines the scenario of these two rules, they should make intuitive sense. The computational process takes the following flow as seen in Fig. 1.

1 P ⇒ positive, N ⇒ negative, B ⇒ big, M ⇒ medium, S ⇒ small, and NIL ⇒ close to zero.

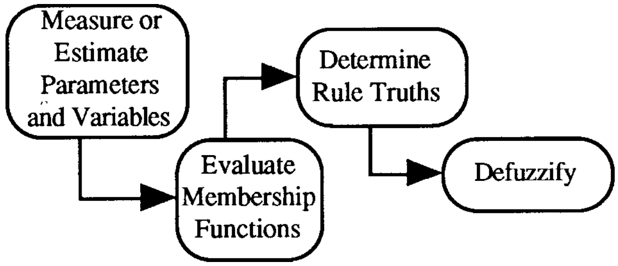

Figure 1: Flow of Rule Computation

Various system parameters and variables are measured or estimated. For each of these parameters, the relevant membership functions are evaluated. For instance, if the lateral displacement, y, is measured to be 0.25 meters, one relevant fuzzy subset is PB. The degree to which y belongs to PB is 0.8 (see Fig. 2; part a). A similar process determines the degree to which y belongs to PS, NIL, etc.

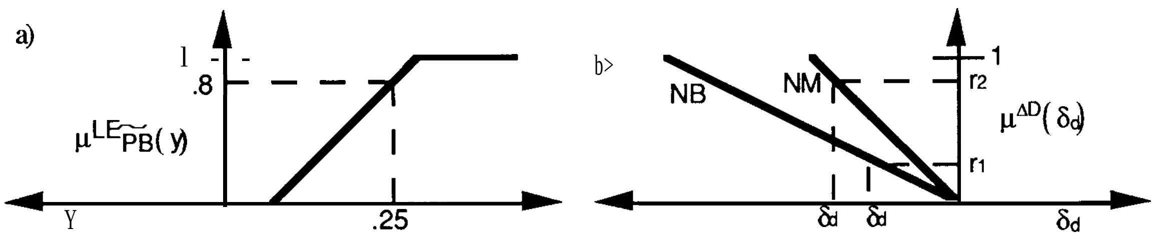

Figure 2: Membership Functions for LE Being PB and AD Being NM, and NB

It should be noted that membership functions can take any suitable form as long as the range interval is [0,1]. However, in our development, we use triangular membership functions which take the form:

$$\mu(y) = \begin{cases} 0 & ; |y-y_0| \geq \alpha \\ 1 - \dfrac{|y-y_0|}{a} & ; \text{otherwise} \end{cases} \quad \text{where } \alpha > 0 \tag{1}$$

A rule *truth* is the degree to which the antecedent is true. This computation for the two rules from above is carried out as follows:

$$r_1 = \min \left\{ \mu^{LE}_{\widetilde{PB}}(y), \max\left[\mu^{CLE}_{\widetilde{PB}}(\delta y), \ \mu^{CLE}_{\widetilde{PS}}(\delta y) \right] \right\}$$

$$r_2 = \min\left\{ \mu^{LE}_{\widetilde{PB}}(y)\,,\, \mu^{\Delta D}(\delta_d) \right\} \qquad (2)$$

where δy implies the change in lateral error between two discrete magnetic markers.

Once each rule truth has been determined, the final step is ***defuzzification***, which is the process of determining a crisp value for δ_d, the front wheel steering angle command, based on the evaluation of the fuzzy rules. A simple method of defuzzification arises if the linguistic terms in the consequence of the rules have monotonic membership functions [10] (see Fig. 2,b). Thus, the value of the rule truth for the antecedents of each rule uniquely determines a crisp value for the consequence (eg. $\delta_{d1} = \mu^{\Delta D}{}_{\widetilde{NB}}^{-1}(r_1)$, $\delta_{d2} = \mu^{\Delta D}{}_{\widetilde{NM}}^{-1}(r_2)$). An over-all value for δ_d can be computed for a set of n rules by:

$$\delta_d = \sum_{i=1}^{n} \delta_{di}\, r_i \Big/ \sum_{i=1}^{n} r_i \qquad (3)$$

This method of defuzzification is called the ***weighted average*** method. Defuzzification concludes the computation of the control law based on the fuzzy rules.

3 Applying Fuzzy Control to Vehicle Guidance

This section discusses the organization and flow of fuzzy rules for vehicle guidance. As mentioned previously, the rule base is broken into four types of rules: a) feedback, b) parameter robustness, c) integral action, and d) feedforward. Figure 3 is the detailed flow diagram which will be referred to throughout this section. At this point crisp and linguistic variables for the vehicle need to be defined to clarify Fig. 3.

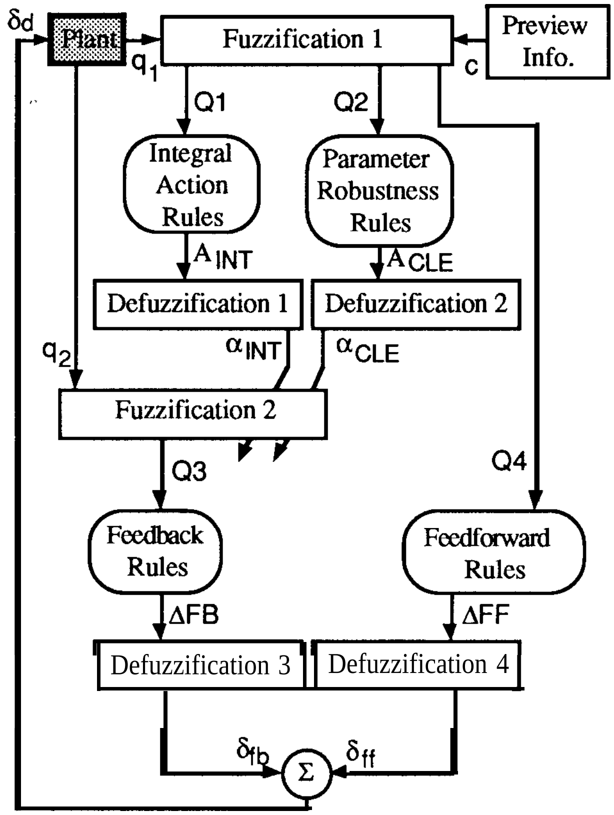

Figure 3: Details of Rule Flow

Two sets (q_1 and q_2) of crisp variables describing vehicle dynamics, which are assumed to be either measured or estimated, are defined as:

$$q_1 \equiv \{ y, v, c_s, \delta_a \}$$

y: Lateral error (meter)

v: Longitudinal velocity (meter/xx)

c_s: Cornering stiffness (Newton/r-ad)

δ_a: Actual Front wheel steering angle of the vehicle (radian)

$$q_2 \equiv \{ y, \delta y, \Sigma y \}$$

y: Lateral error (meter)

δy: Change in lateral error between two discrete magnetic markers (meter)

Σy: Sum of lateral error; summed at each discrete magnetic marker (meter)

In addition, preview information provides the location, direction and magnitude of an upcoming road curvature, c, which is, by definition, the reciprocal of the radius of curvature, p.

The command signal to the vehicle is δ_d, the front wheel steering angle, given as $\delta_d = \delta_{fb} + \delta_{ff}$, where:

δ_{fb}: Front wheel steering angle command from feedback rules (radian)

δ_{ff}: Front wheel steering angle command from feedforward rules (radian)

We now change directions, defining sets of linguistic variables. The set $Q1 \equiv \{ \text{LEN}, \Delta\text{AN} \}$ as referred to in Fig. 3 is made up of linguistic variables used in the premises of the "Integral Action Rules". These variables are defined as follows:

LEN: Average lateral error, y, of last **N** markers

ΔAN: Average actual front wheel steering angle, δ_a, of last **N** markers

As will be discussed in Section 3.3, LEN and ΔAN can detect a slight (not previewed) road curvature or an external disturbance such as low frequency side-winds.

The second linguistic variable set, $Q2 \equiv \{ V, CS \}$, consists of inputs to the "Parameter Robustness Rules", where

V: Longitudinal velocity, **v**

CS: Cornering stiffness, c_s

The third linguistic variable set, $Q3 \equiv \{ LE, CLE, INT \}$, is made up of inputs to the heart of the fuzzy rule based controller, the feedback rules, where

LE: Lateral error, **y**

CLE: Change in lateral error, δy

INT: Sum of lateral error, Σy

The set $Q4 \equiv \{ V, CRV \}$ is made up of linguistic variables used in the premises of the "Feedforward Rules", where

CRV Product of velocity and curvature, CV, (c is provided by preview information).

Note that CRV is a curvature factor based on both the vehicle speed and curvature. When CRV is "big", the curve is relatively sharp. The general flow begins by evaluating the "Integral Action Rules" and the "Parameter Robustness Rules" in order to adjust the membership functions for the fuzzy subsets used to evaluate the "Feedback Rules". Meanwhile, the "Feedforward Rules" act in parallel with the rest of the system. The details of Fig. 3 will be discussed in the subsequent sections.

3.1 Feedback Rules

Concepts of the feedback module of the rule base are analogous to a conventional feedback control loop. The rules consider as input the current and past conditions of measured or estimated parameters and decide on an appropriate steering angle. The specific linguistic input variables are LE, CLE, and INT. There are 25 core rules which place heavy emphasis on LE and CLE. Since the plant is an inertial system, LE acts as proportional feedback while CLE provides derivative feedback and INT is the integral term. The development of these 25 rules are based on heuristic and engineering judgement regarding vehicle operation. The tracking objectives of these rules are similar to classical control theory goals such as small rise time, small settling time, and small overshoot. However, these goals must be relaxed somewhat since humans prefer smooth transitions while maneuvering a vehicle. Thus, a tradeoff is apparent.

Simulations show that LE and CLE are sufficient for lane tracking in straight sections of roadway in the absence of disturbances such as a side-wind. However, the additional linguistic variable INT is an important variable necessary to eliminate steady state error when disturbances are present or when the roadway deviates slightly from being perfectly straight (where the system would *not* be notified by preview curvature information). The INT variable is closely associated with the "Integral Action Rules" (see Fig. 3) and will be discussed in detail in Section 3.3 .

3.2 Parameter Robustness Rules

The vehicle speed, V, is clearly an important variable in lateral guidance. The system is much more responsive to the input, δ_d, at higher speeds. The linguistic input variable (to the "Feedback Rules") that is most affected by changes in V is CLE. Thus, it makes intuitive sense that the control system should have more damping when the vehicle speed is high (for instance, in classical control we might increase the derivative gain). In a fuzzy rule based controller, the sensitivity of the closed loop system response to CLE can be changed by adjusting the membership functions of its fuzzy subsets. Consider the thick lines of Fig. 4, which displays the membership functions for the five fuzzy subsets which describe CLE when V is small (SM).

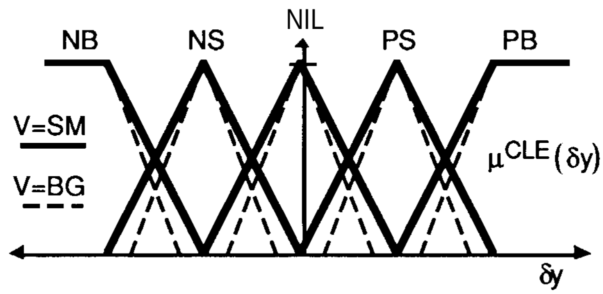

Figure 4: Membership Functions for CLE

Noting the expression for triangular membership functions (Eq. 1) and the defuzzification procedure (Eq. 3), decreasing α_{CLE} will increase the sensitivity of CLE to final control output, δ_{fb}, which is analogous to increasing the derivative gain in a classical controller. Recalling the "Parameter Robustness Rules" of Fig. 3, V is a linguistic input variable. The linguistic consequent to these rules is A_{CLE}, which yields α_{CLE} after "Defuzzification 2", which in turn adjusts the membership functions for CLE, used in "Fuzzification 2". The idea is to decrease α_{CLE} when V is big (BG), (note the dashed lines of Fig. 4).

The final linguistic variable considered in the "Parameter Robustness Rules" is the cornering stiffness, CS. The parameter, c_S, is estimated by the least squares estimation procedure [11]. A smaller value of c_S implies that the road surface conditions are slippery. The response of the closed loop system in slippery conditions is oscillatory in comparison to dry conditions. Thus, similar to variations in v, the "Parameter Robustness Rules" use CS to adjust α_{CLE}.

3.3 Integral Action Rules

The purpose of the "Integral Action Rules" is to detect from parameter conditions if and how much integral action is necessary. Recall from Section 3.1 that a perfectly straight, level roadway with no external disturbance would need no integral action. However, consider a special case of a constant side-wind disturbance. At steady state the lateral position of the vehicle, y, would be slightly downwind and the actual front wheel steering angle, δ_a, would be slightly turned into the wind. These two variables are used in the "Integral action Rules" (see Fig. 3) with the corresponding linguistic variable set, $Q1 \equiv \{LEN, \Delta AN\}$. In actuality these linguistic variables use as base variables an average over N magnetic markers of y and δ_a. The consequent of the "Integral Action Rules" is A_{INT}, which corresponds to α_{INT} after "Defuzzification 2" (see Fig. 3). Thus, in a similar manner to α_{CLE}, either an external disturbance or slight, not previewed curvature would result in a smaller A_{INT}, which makes "Feedback Rules" more sensitive to the integral term of lateral displacement.

As a final implementation note to this section, one might ask if the system performance degrades by the "Integral Action Rules" when the system response is in a highly transient state, confusing the "Integral Action Rules" as to the true meaning of the linguistic values of LEN and ΔAN. Since these variables are only meaningful at close to steady state conditions (ie. low frequency), a variance of $\dot{y}$ and δ_a over N markers must be below respective threshold variances in order to be declared useful.

3.4 Feedforward Rules

Feedforward action is used to assist the controller when the vehicle engages a curved section of roadway, which is known in advance by the controller via preview information. Essentially, an offset of front-wheel steering angle or feedforward term, δ_{ff}, (which corresponds to vehicle speed, v, and the curvature, c) is added to the steering angle determined by the feedback controller, δ_{fb}, to give δ_d (see Fig. 3). Two questions arise about this issue, 1) how large should δ_{ff} be given v and c ? and 2) the more difficult question, what should the transition be from the straight to curved transition and from the curved to straight transition?

In [1 1] a relationship between δ_{ff} and the pair, v and c, is suggested to be:

$$\delta_{ff} = \frac{m(l_2 - l_1)\, v^2 + 2\,(l_2 + l_1)^2\, c_s}{2\,(l_2 + l_1)\, c_s}\, c \tag{4}$$

where m is vehicle mass and l_1 and l_2 are the distances from the center of gravity of the vehicle to the front wheel base and the rear wheel base, respectively. In this investigation we assume mass variations are insignificant and that c_s corresponds to dry road conditions.

The relevant membership functions of fuzzy subsets and the subsequent feedforward rules for δ_{ff} are developed by studying Eq. 4. To do this we consider a variable, CRV, to describe sharpness. The membership functions for CRV (BG, MD, and SM) have a base variable, c*v. Note that these fuzzy subsets describe a curve in one direction, but the process has a mirror image for the opposite direction. The linguistic variable V is also considered in the "Feedforward Rules" as V takes on linguistic values BG, MD, and SM. Seven rules are developed using CRV and V in the premises with the consequence being **AFF.**

The most difficult task in tracking severe curvatures is achieving a smooth implementation of the feedforward term in the transition from a straight section of roadway to an abrupt, constant curvature section, and visa versa. It has been proposed that human drivers anticipate curvature changes in the roadway and initiate front wheel steering action into the curve approximately 1 second before the curve actually starts [5],[6]. Based on this theory, our choice of implementation of the feedforward front-wheel steering term takes the form of Fig. 5:

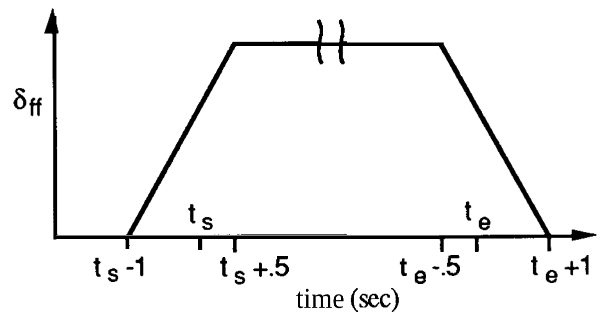

Figure 5: Feedforward implementation

where t_s is the time when the curve begins and t_e is the time when the curve ends. Note that the distance where the feedforward term begins, before the curve change, is dependent on the velocity of the vehicle.

4 Simulation Results

The purpose of these simulations are 1) to show the positive performance of the fuzzy rule based controller and 2) to show improvements in the performance when rules are added to combat variations in system parameters and external disturbances. A logical starting point is to show the nominal case of tracking a straight line under nominal conditions. A complex, nonlinear model [11] is used for the simulation. The 1550 kg. vehicle is simulated traveling at 30 m/s in dry conditions ($c_s/\hat{c}_s = 1.0$, where $\hat{c}_s$ is the nominal cornering stiffness for dry roads) entering the controlled lane with y = 0.1 meters, and all derivatives of y, the yaw angle, and all its derivatives equal to zero. Figure 6 shows the displacement response as a function of time for the nominal case using ***only*** feedback rules (ie. no adaptation from the "Integral Action Rules" or the "Parameter Robustness Rules").

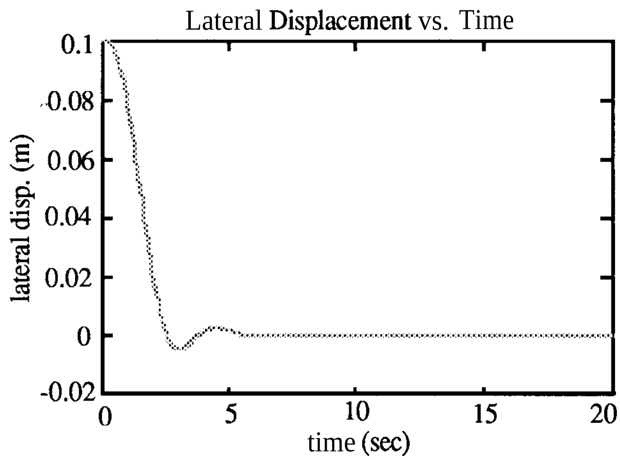

Figure 6: Nominal Conditions

The next issue we address is variations in vehicle speed. First we consider a faster velocity, 40 m/s. Without adaptation from the "Parameter Robustness Rules", the system exhibits more overshoot than the nominal speed of 30 m/s, as can be seen from the solid line simulation of Fig. 7.

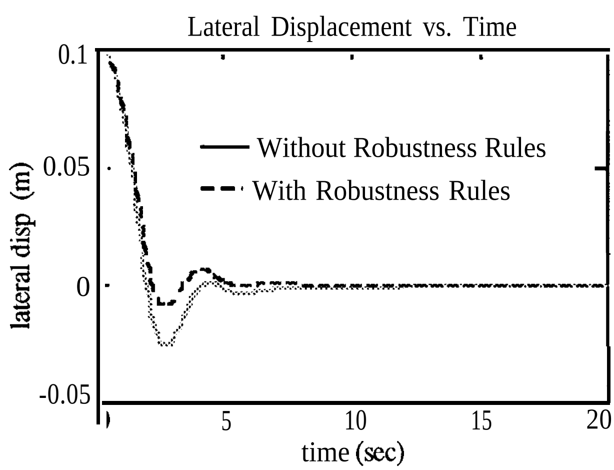

Figure 7: High Vehicle Speed

However, when the "Parameter Robustness Rules" are invoked, this overshoot is reduced (see the dashed line).

Conversely, when the speed is reduced to 20 m/s, the closed loop system response has too much damping without the "Parameter Robustness Rules" (note the solid line in Fig. 8).

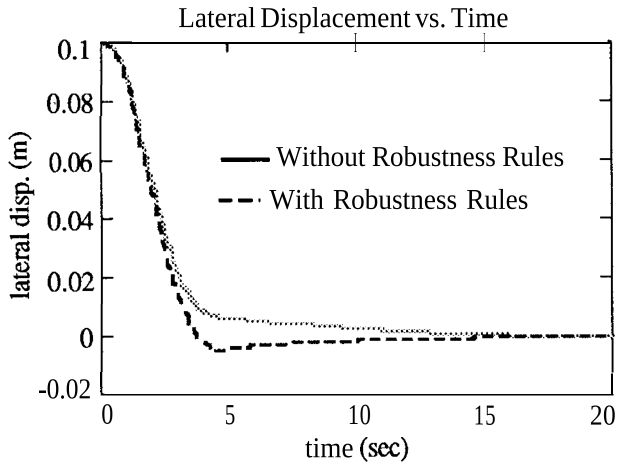

Figure 8: Low Vehicle Speed

The dashed line of Fig. 8 shows the improvement of the "Parameter Robustness Rules" at a reduced speed.

Next, we turn our attention to the traction conditions between the roadway and tires. Using an extreme slippery condition of $c_s/\hat{c}_s = 0.3$, with all other parameters at nominal values, the solid line of Fig. 9 shows that the system response has nearly 50% overshoot, when the "Parameter Robustness Rules" are not used.

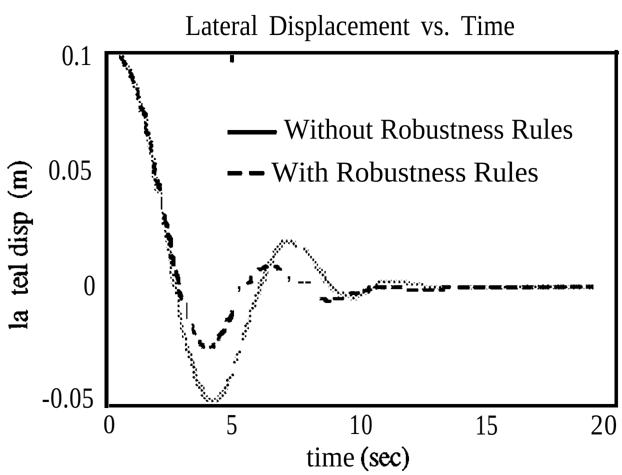

Figure 9: Slippery Conditions

However, the dashed line of Fig. 9 shows a significant reduction in the overshoot of the system response when using the "Parameter Robustness Rules" simulated in slippery conditions.

Suppose the vehicle is operating under nominal conditions with an external disturbance in the form of a stiff side-wind of approximately **25 m/s**. If we recall that our plant is an inertial system and **y** feedback provides proportional control while δy feedback provides derivative control, we can see from the solid line of Fig. 10 that a side-wind results in a steady-state error when no integral action rules are used (ie. Σy is not used as feedback to the controller). Note that the initial conditions are the same as previous simulations, with the exception that y is also initialized to 0.0. Also, the disturbance begins at 2 seconds into the simulation and remains constant.

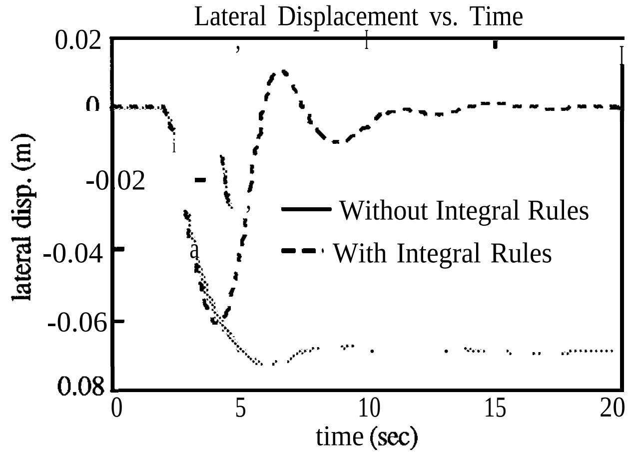

Figure 10: Wind Disturbance

Note the elimination of the steady-state error when the "Integral Action Rules" are invoked to determine the strength of the integral action needed and to implement the integral action in the "Feedback Rules" (see dashed line of Fig. 10). As time passes, parameters settle on steady state values. The steady-state front-wheel steering angle to combat this disturbance is 0.012 degrees.

At this point we have an overlap of issues. Instead of an external disturbance on a straight roadway, we consider a slightly curved roadway with no external disturbance. The result of this slight curvature is similar to the case of a side-wind disturbance. There is a steady-state error if no integral action is used (see the solid line in Fig. 11). Note that the initial conditions are the same as the previous (wind disturbance) simulation, and a slight curvature, $c = \frac{1}{20000}\ \text{meter}^{-1}$, begins at 2 seconds into the simulation.

Although feedforward action could be used to handle this situation, we choose to use the "Integral Action Rules" to detect such curves and eliminate the steady-state error. The reason for this choice is that it is not efficient to encode as preview information every severity of curvature since the number of fuzzy subsets and rules would become numerous, especially when the "Integral Action Rules" are capable of dealing with small curvatures. The use of the "Integral Action Rules" is demonstrated by the dashed line of Fig. 11. The steady-state front-wheel steering angle for this simulation is 0.01 degrees.

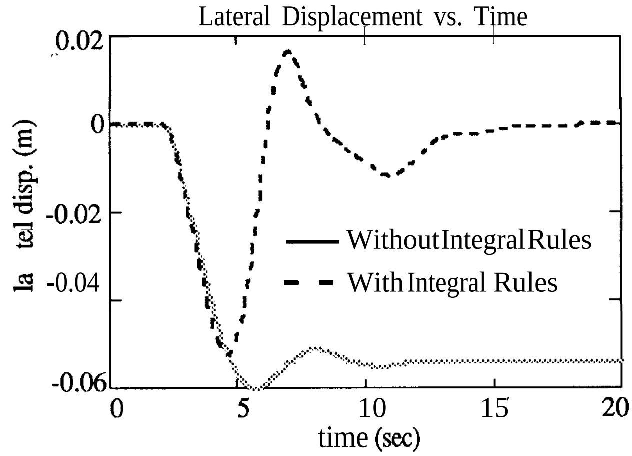

Figure 11: Slight Curvature

The final simulations consider severe curvature changes whose direction, magnitude, and duration are known to the controller as preview information. The initial conditions of the lateral and yaw motions are all zero, and the curvature begins at 2 seconds into the simulation and ends at 15 seconds of the simulation. Figure 12 shows the lateral displacement response for the nominal case (ie. 30 m/s velocity) and the maximum constant curvature, $c = \frac{1}{650}$ meter-l, (as prescribed by the California Department of Transportation for this velocity).

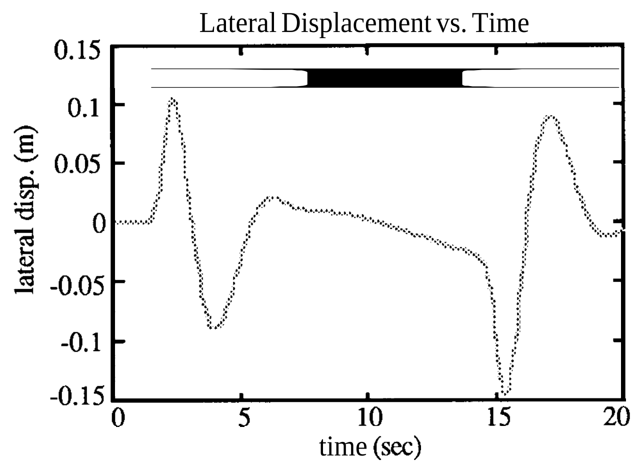

Figure 12: Severe Curvature, v=30m/s

The controller initiates front wheel steering action into the curve 1 .O second before the curve begins, which accounts for the initial 0.1 meter lateral displacement on the inside of the curve. Note that the front-wheel steering feedforward term begins at zero, 1 .O second before the curve begins, and increases linearly with time, ending at the steady state feedforward term 0.5 seconds after the curve transition. The infinite change in curvature accounts for the second 0.15 meter lateral displacement on the outside of the curve. The combination of the "Feedforward Rules" and the "Integral Action Rules" drive the lateral displacement, y, to zero at the steady-state portion of the curve. The length of the curve in this simulation is not long enough to reach steady-state. However, given enough time, lateral displacement would converge to zero. As a final note, the transition from a curved roadway back to a straight roadway is treated by the fuzzy controller as a mirror image.

To complete' the set of simulations over the range of vehicle speeds and their corresponding maximum curvatures, see Fig. 13, which shows a 20 m/s velocity at $c = \frac{1}{260}$ meter^{-1}

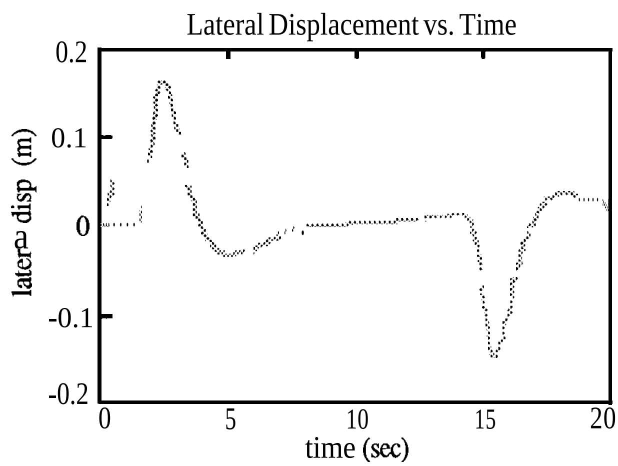

Figure 13: Severe Curvature, v=20m/s

and Fig. 14, which shows a 40 m/s velocity at $c = \frac{1}{2200}$ meter^{-1}.

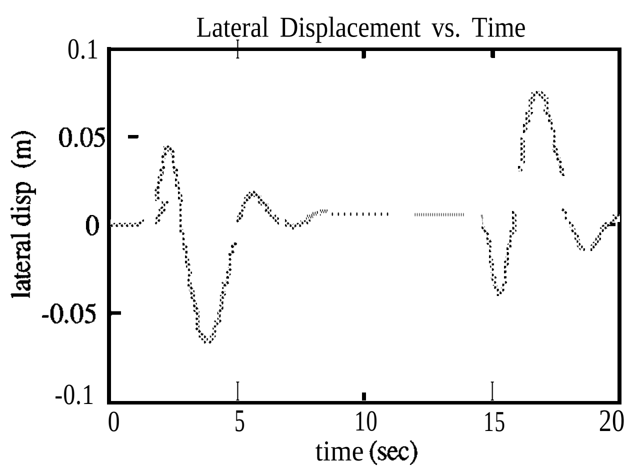

Figure 14: Severe Curvature, v=40m/s

These simulations show similar trends.

5 Conclusion

This paper considered the application of a fuzzy rule based controller to lateral guidance of a vehicle on an automated highway. The flexible characteristics inherent in fuzzy logic is demonstrated by designing and simulating a fuzzy rule based controller to achieve "good" tracking of the vehicle to the center of a lane, while being robust to external disturbances and parameter variations of the vehicle. In addition, the fuzzy rule based controller handles a large number of input variables in an effective manner.

Current investigation considers feedback of vehicle yawrate as a linguistic variable to the fuzzy rules. Yawrate feedback has been shown to enhance system performance in control theoretic techniques [12]. Furthermore, an investigation is under way to compare the performance of the fuzzy rule based control approach to control theoretic techniques [7], [8].

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