

A Fuzzy Inference System for Understeer/Oversteer Detection Towards Model-Free Stability Control

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ABSTRACT

In this paper, a soft computing approach to a model-free vehicle stability control (VSC) algorithm is presented. The objective is to create a fuzzy inference system (FIS) that is robust enough to operate in a multitude of vehicle conditions (load, tire wear, alignment), and road conditions while at the same time providing optimal vehicle stability by detecting and minimizing loss of traction. In this approach, an adaptive neuro-fuzzy inference system (ANFIS) is generated using previously collected data to train and optimize the performance of the fuzzy logic VSC algorithm. This paper outlines the FIS detection algorithm and its benefits over a model-based approach. The performance of the FIS-based VSC is evaluated via a co-simulation of MATLAB/Simulink and CarSim model of the vehicle under various road and load conditions. The results showed that the proposed algorithm is capable of accurately indicating unstable vehicle behavior for two different types of vehicles (SUV and Sedan). The algorithm can do this without any significant parameter adjustment, illustrating its robustness against the considered uncertainty.

CITATION: Hirche, B. and Ayalew, B., "A Fuzzy Inference System for Understeer/Oversteer Detection Towards Model-Free Stability Control," *SAE Int. J. Passeng. Cars - Mech. Syst.* 9(2):2016, doi:10.4271/2016-01-1630.

INTRODUCTION

Vehicle stability control systems are a key factor in reducing the number of road fatalities. The National Highway Traffic Safety Administration (NHTSA) estimates a total of 1,144 lives saved in 2012 by VSC systems [1]. It is therefore not surprising that extensive research has been conducted to improve the workings of these systems [2]. However, current systems heavily rely on linearized planar vehicle models for sideslip and direct yaw moment control (DYC) using brake intervention [3]. These models use predefined vehicle parameters such as vehicle weight or tire lateral stiffness. In reality these parameters are subject to change, thus reducing the optimal operation point of these model-based VSC systems to a narrow window of road and load conditions. This also causes a considerable amount of tuning effort during the development process of VSC algorithms for production vehicles. Every new prototype stage or configuration will have a new weight distribution, tire parameters, or suspension alignment which makes it necessary to adapt the VSC algorithm. Hence, more robust algorithms are necessary [4]. Early approaches to compensate for nonlinearities and uncertainties used adaptive controllers [5] or H_∞ control theory [6]. Arat et al [7] treated the degradation of performance from model-based systems due to estimation errors during evasive maneuvers. They proposed a sensor fusion approach that can estimate tire slip angle under varying surface friction conditions. Dengo et al [8] used

model predictive control to calculate the amount of steering angle and stabilizing yaw moment (DYC). An optimal allocation algorithm is then designed to generate this yaw moment. Their algorithm showed promising results in terms of performance but lacked in robustness considerations.

In recent times, fuzzy logic-based approaches have proven to outperform advanced model-based control algorithms in industrial applications where models are inaccurate or not available. Fuzzy logic uses human linguistic reasoning and possibility distributions instead of traditional binary logic and allows for model uncertainty by imposing generalized rules [9]. Junwei et al and Uzunsoy combine a conventional yaw and side-slip angle tracking algorithm with fuzzy logic instead of a PID controller. By doing so they reduce the amount of tuning that is necessary to adjust PID characteristics, such as overshoot and settling times, while at the same time making the controller more robust against parameter changes such as load conditions or estimation errors from side-slip estimators or road friction estimators [10] [11]. Kaldas et al [12] and Rao et al [13] used fuzzy logic to control the vertical dynamics of suspension systems. Since the input to suspension systems is difficult to measure model-based controls are difficult to implement. A comparison with passive and model-based LQR controlled suspensions showed vast improvements in ride and dynamic tire load over a wide range of road inputs [13] [12].



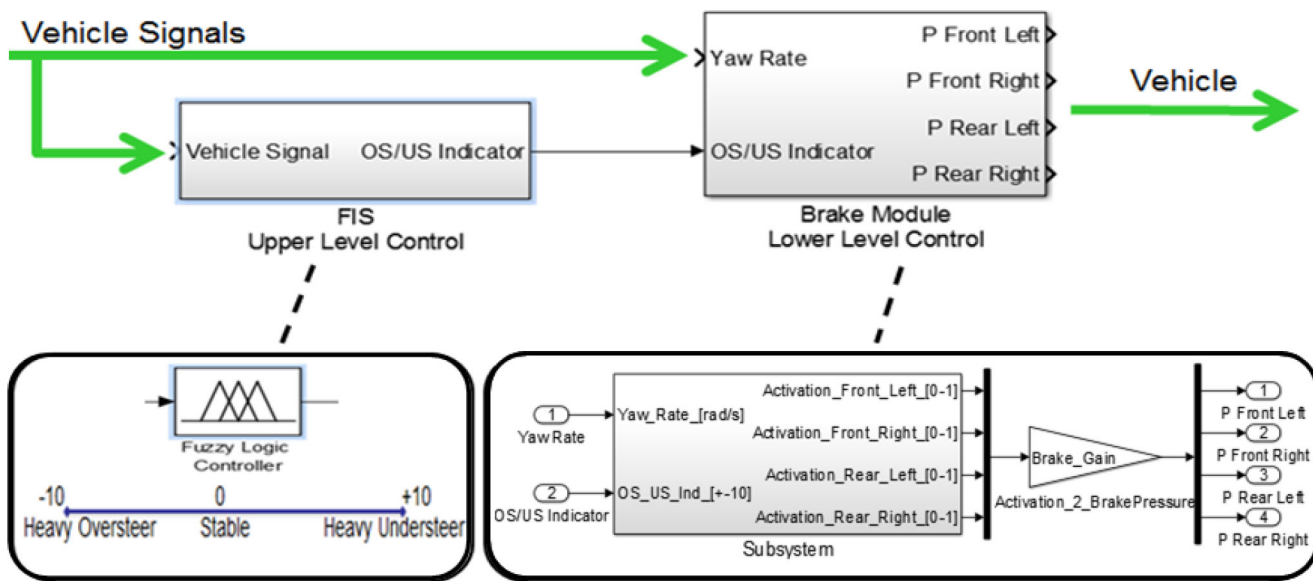


Figure 1. VSC Architecture: Brake-Based Implementation

Even though previous approaches have shown good results in dealing with model uncertainty and external inputs, there are a few drawbacks to be addressed. The key component of every fuzzy-inference system (FIS) is a set of if-then rules that mimic human knowledge and reasoning for the problem at hand. The FIS, unlike a human operator, cannot learn and adapt to changing external conditions without extensive training or adaptation [14]. Previous approaches have tried to generate arbitrary if-then rule sets and use adaptation algorithms to give the FIS system a means to optimize itself without supervision [12].

The approach proposed in this paper uses fuzzy-inference systems towards a model-free design of vehicle stability control systems. It builds on Anderson and Law's [15] approach of a fuzzy logic stability control that uses measurable vehicle signals instead of estimation algorithms and parameterized models. In this paper, we propose soft computing techniques to generate an adaptive neuro-fuzzy inference system (ANFIS), a rule set that can be trained to characterize a desired vehicle behavior. Deviations from the desired vehicle behavior are categorized as understeer or oversteer on a scale of +10 to -10. An optimized ANFIS system has the potential to simplify and unify the vehicle stability control design process for different vehicle classes by removing reliance on vehicle specific and potentially changing parameters such as tire properties, center of gravity location, and dimensions.

The paper will focus on the discussion of the design and illustration of the robustness of this upper level detection of understeer or oversteer. A simple lower level brake force allocation algorithm will be used to compare the control performance against conventional systems. The model-free VSC is implemented in Matlab/Simulink® and co-simulated with two CarSim® vehicle models. The vehicle models represent two different types of vehicles, 1) a SUV, and 2) a Sedan. The performance of the model-free VSC is evaluated in simulations of a standardized ECE R13H Sine with Dwell test [16].

MODEL-FREE VSC ARCHITECTURE

The structure of the model-free VSC is shown in Figure 1. Conceptually, the implementation is organized hierarchically as upper and lower level control. The fuzzy detection stage in the upper level control uses vehicle signal inputs, like longitudinal vehicle speed (V_x), lateral acceleration (A_y), yaw rate (A_{vz}), and road wheel angle (RWA), to detect and categorize unstable vehicle oversteer (OS) or understeer (US) events. This is done in a single FIS. The output is one final indicator that categorizes the unstable situation on a scale of -10 for heavy oversteer to +10 for heavy understeer. Logically, 0 stands for a neutral stable vehicle. In the lower level control, responsible for allocation of the stabilizing yaw moments, the activation module uses the stability indicator from the detection stage and combines it with the yaw rate signals to decide which wheel to brake. The activation signal, which is proportional to the OS/US indicator is then fed through a proportional gain to convert the ± 10 OS/US indicator signal to brake caliper pressures.

A companion paper by the authors [17] focuses on an active steering-based implementation of the lower-level of the VSC using the FIS for upper-level OS/US detection detailed in the following sections of this paper.

FUZZY OS/US DETECTION

An important task in modern VSC control systems is to reliably detect unstable events. The reliability here is one of the key factors towards customer satisfaction. VSC systems with misdetections or overly sensitive systems limiting the vehicles cornering capacity too early lead to customer complaints. The same applies to systems that are missing to detect unstable events, where the latter is not just a customer complaint but also a safety issue. Therefore, a VSC system has to detect unstable events early enough to be able to stabilize the vehicle, with the least amount of misdetections to satisfy the customer. It is believed that model-based approaches are immune to such misdetections because possible mismatches between reference

model used for control and the actual vehicle. The goal for the model-free structure is to eliminate reliance on models for US/OS detection by using fuzzy logic modeling.

The FIS of the model-free VSC utilizes various vehicle signals, evaluates them and returns one combined oversteer/understeer number (OS/US Indicator) between -10 and +10 to indicate unstable events of various severity. The FIS module we propose uses five vehicle signals steering wheel angle (SWA), steering wheel rate (SWRATE), yaw rate (AVZ), yaw acceleration (AAZ), and lateral jerk (AAY). The first four signals are commonly used in conventional VSC approaches as well. The lateral jerk signal was included to identify the OS pattern (see Figure 3). It is the derivative of the lateral acceleration and goes to zero when the lateral acceleration peaks out (saturates).

We adopt the Sugeno-based FIS, which uses 5 membership functions to fuzzify each of these input signals. The membership functions were not generated arbitrarily as in previous approaches. A combination of subtractive clustering and optimization lead to their shape and orientation. As a result of the optimization, 7 rules are retained that combine the 5 fuzzified inputs and generate a single OS/US Indicator between -10 and +10. Figure 2 shows an example of the detection process. Here, the two rules “If yaw rate (AVZ) is high and steering wheel angle (SWA) is medium then Indicator is high negative” and the rule “If yaw rate (AVZ) is medium then Indicator is 0” are combined. For the inputs of 30 deg/s yaw rate and 40 deg steering wheel angle, the two rules result in a final OS/US indicator of -5, indicating considerable oversteer.

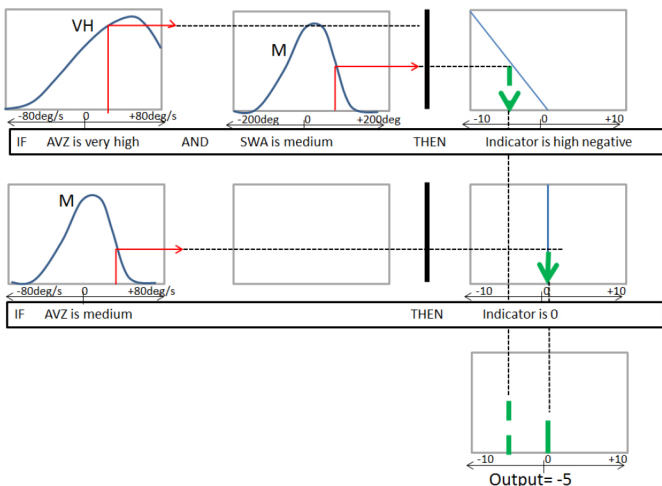


Figure 2. VSC OS/US Detection Process Example

The next section will explain in more detail how the membership functions and rules were chosen and optimized.

DESIGN OF OS/US DETECTION

Initial research into vehicle behavior during oversteer (OS) maneuvers indicated that there is a pattern in yaw rate and lateral acceleration displayed during most OS situations. Figure 3 illustrates such a behavior during a constant speed Sine with Dwell (SwD) maneuver. This vehicle shows heavy oversteering behavior after 2 seconds into the maneuver. Comparing the signals of lateral acceleration and yaw

rate right before and right after 2 s one can see a clear pattern. Right before, the yaw rate follows the lateral acceleration; even though the absolute values are different, the pattern is similar. Right after two seconds, the lateral acceleration is constant, its jerk close to zero, indicating tire saturation. At the same time, the yaw rate changes rapidly. This behavior is displayed right after oversteer begins. However, it is desired to detect oversteer as early as possible. The optimal scheme could detect oversteer already in the buildup phase. This way the actuators have enough time to stabilize the vehicle.

To generate the optimal set of rules that approach such an ideal detection, an adaptive neuro fuzzy inference system (ANFIS) is adopted that can automatically train the fuzzy logic (membership functions & rules) that detects understeer and oversteer. This is detailed below.

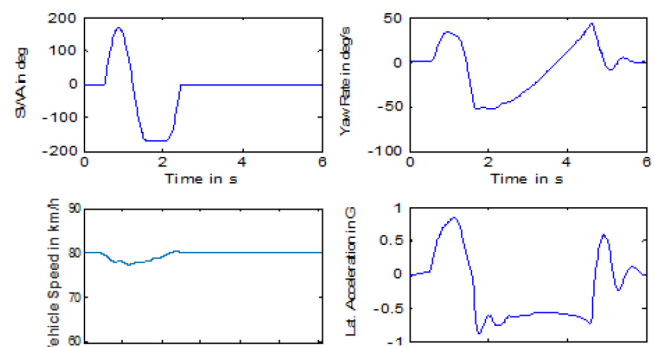


Figure 3. An Example OS Pattern, SUV, SwD @ 80km/h, 169 deg max. SWA, Mu=0.9, no VSC

GENERATING TRAINING DATA

The first step in training the fuzzy logic is to generate a set of input/output data. The input data consists of vehicle signals that can be used to determine and evaluate unstable situations. Recall that Figure 3 shows the pattern for OS detection. The first four signals are yaw rate, yaw acceleration, steering wheel angle, and lateral jerk. Excessive yaw rates indicate oversteer while small yaw rates combined with high steering angles indicate understeer. The combination of non-zero yaw acceleration and close to zero lateral jerk represent the identified OS pattern in Figure 3. Furthermore, the steering rate is used to indicate counter steer intentions of the driver. The output data consists of the desired OS/US Indicator for the set of input signals at hand. This is a tuning parameter for the control mechanism. Using different methods to determine the desired output will result in different fuzzy logic schemes. Changing the desired output is a way to set up the vehicle behavior, e.g. more understeering for rear wheel driven vehicles or to reduce the inherent understeer tendency of front heavy vehicles (sport mode).

The importance of the training data cannot be over emphasized. Not only is the content of the data itself important for the calculation of the desired output, but also the amount of training data is important. Too much training data can make it impossible for the ANFIS algorithm to minimize the error function to an acceptable level, resulting in spiky outputs and overly sensitive OS/US indicators or overtraining. On the other hand, not enough training data means not enough maneuvers, can mean that the training is insufficient. This