An Adaptive Lateral Preview Driver Model

Ali.Y. Ungoren[1] and Huei Peng[2]

SUMMARY

Successful modeling and simulation of driver behavior is important for the current industrial thrust of computer-based vehicle development. The main contribution of this paper is the development of an adaptive lateral preview human driver model. This driver model template has a few parameters that can be adjusted to simulate steering actions of human drivers with different driving styles. In other words, this model template can be used in the design process of vehicles and active safety systems to assess their performance under average drivers as well as atypical drivers. We assume that the drivers, regardless of their style, have driven the vehicle long enough to establish an accurate internal model of the vehicle. The proposed driver model is developed using the adaptive predictive control (APC) framework. Three key features are included in the APC framework: use of preview information, internal model identification and weight adjustment to simulate different driving style. The driver uses predicted vehicle information in a future window to determine the optimal steering action. A tunable parameter is defined to assign relative importance of lateral displacement and yaw error in the cost function to be optimized. The model is tuned to fit three representative drivers obtained from driving simulator data taken from 22 human drivers.

1. INTRODUCTION

In Year 2000, more than six million motor vehicle crashes occurred in the US [1]. These accidents are the results of complex interactions between the driver, vehicle, and the environment. A study sponsored by NHTSA found that driver error was the major contributor in more than 90% of the crashes they examined [2]. Furthermore, drivers could exhibit vastly different response under the same driving task. It is thus very important for automotive engineers and designers of vehicle active safety systems to understand, and simulate human driving behavior accurately. Computer simulations provide an efficient means to analyze the interaction between the human driver and the vehicle, even before a vehicle or its sub-systems are produced. This "virtual proving ground" is especially important for the development of active safety systems, or vehicle limiting-performance assessment, because of the cost and safety issues related to conducting near-crash testing on real vehicles with real human drivers.

The increased popularity of Sport Utility Vehicles (SUV) in the last decade prompted closer scrutiny of their roll performance, because of their poor showing in rollover crash data. NHTSA, the US government agency overseeing motor vehicle safety, is currently developing a new dynamic testing procedure to assess the rollover

[1] Ph.D. Student
[2] Corresponding author, Associate Professor, Department of Mechanical Engineering, University of Michigan, Ann Arbor, MI 48109-2133, Tel:734-936-0352, Fax:734-764-4256, hpeng@umich.edu

propensity of light ground vehicles. This critical safety issue inspires our interest in understanding human steering actions and the development of a driver model suitable for high lateral acceleration applications.

Test maneuvers to assess vehicle handling and roll characteristics can be divided into two types: “Open loop” and “Closed loop”. In open loop tests, time trajectories of inputs are pre-defined (e.g. J-Turn, Fishhook). In other words, the inputs are not dependent on the response of the vehicle. These tests can be performed with a steering and speed control robot, and thus can be done with high repeatability. In closed loop tests, the vehicle needs to be manipulated to follow a pre-defined path with acceptable accuracy. Theoretically, an automatic steering robot can be used for closed loop tests as well. However, a reliable road-sensing system can be quite expensive, and the control algorithm needs to approximate human actions under these high-lateral acceleration scenarios. Due to these difficulties, the closed loop tests are mostly performed by professional drivers on a test track delineated by orange cones. Closed loop tests are used by many car companies to test real world driving scenarios. Because human drivers are used, however, these tests are not quite repeatable and it is hard to draw concrete conclusions from the test results, for example, to compare the performance of different vehicles (even though some pretend they can do so to 1mph accuracy). The practice of using outriggers also makes the tests results somewhat questionable.

Recent advances in active vehicle control systems further elevate the importance of closed loop tests. Many of these control systems were designed to ensure that vehicles operate within a defined safe region, and thus inevitably interact with human driver. Open loop tests ignore human/control system interactions and thus only provide limited useful information. For example, Vehicle Stability Control (VSC) systems are designed to enhance vehicle handling, path keeping, and roll characteristics. Under a severe moose-test, VSC should limit the vehicle side slip angle, but in the meantime should not make the vehicle so understeer that its path following performance is jeopardized. Due to the cost, process and safety concerns, however, it may not be practical to perform field testing. Simulation assessment thus may be more practical for certain situations. A key requirement for closed-loop vehicle simulations is the development of a driver model that is valid at high lateral acceleration levels, which is the focus of this paper.

2. LITERATURE REVIEW

2.1 Human-Machine Interactions

When a human interacts with a machine, or more specifically, is driving a vehicle, it is widely believed that s/he first plans for a desired response trajectory, which is converted into appropriate commands to be generated by the neural muscular system. A number of studies [3, 4] suggested that human maintains an internal representation of the dynamic system (internal model), not in a complex mathematical form, but simple mapping from desired movement to corresponding command (the inverse model, see Figure 1) [5].

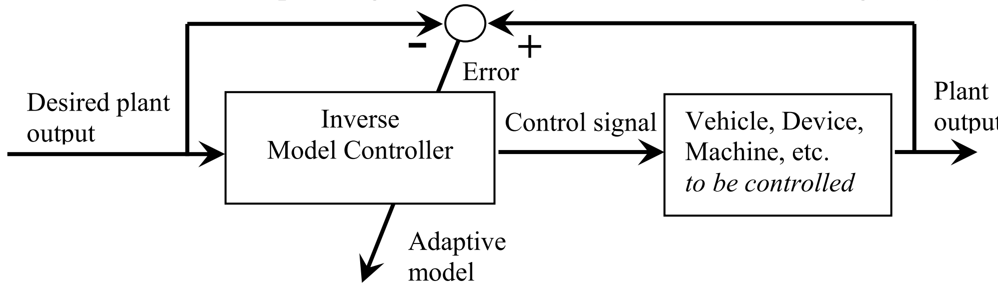

Figure 1: Basic structure for adaptive inverse control technique.

The internal model or the inverse model is hypothesized to be learned over time, becoming more accurate by using the mismatch between the target response and the actual response. When we mimic this process to develop a human model that can be implemented, a proper model structure first needs to be determined. Time-series representations or nonlinear mappings (e.g. neural networks) can then be obtained by using input/output data to achieve optimized model performance.

Another seemingly different modeling philosophy [6, 7] suggests that the human uses forward models (Figure 2) to predict the machine response, possibly over a future horizon, and then make decisions based on expected future response and desired machine output. The forward models are simple, possibly only capture the steady-state gain and a low order approximation of the plant. The simple mathematical model is by no means contradicting to the inverse model described above. In fact, the forward model is just another way of using one's knowledge about the plant model.

A general architecture, which uses the plant model in two different ways, is suggested in [5, 8] to explain the human motions. The basic idea of this methodology is shown in Figure 3. In this architecture, human motor control actions are divided into three parts [9]: precognitive, pursuit, and compensatory. In this formulation, a forward model is used in a compensatory block to provide the driving input to the system only if there are residue plant dynamics that are not compensated for by the actions of the inverse model (in the pursuit and pre-cognitive modules). In other words, when the precognitive behavior or the inverse model is perfect, the compensatory module does not contribute to the system response. Under this situation, the human operator generates neuromuscular commands resulting in system outputs which are exactly as desired. Once perfected, these neuromuscular commands are stored in a repertoire for future use. These pure open-loop control actions are often classified as forms of precognitive behavior. The relative importance of the three control actions is obviously task and repetition (experience) dependent.

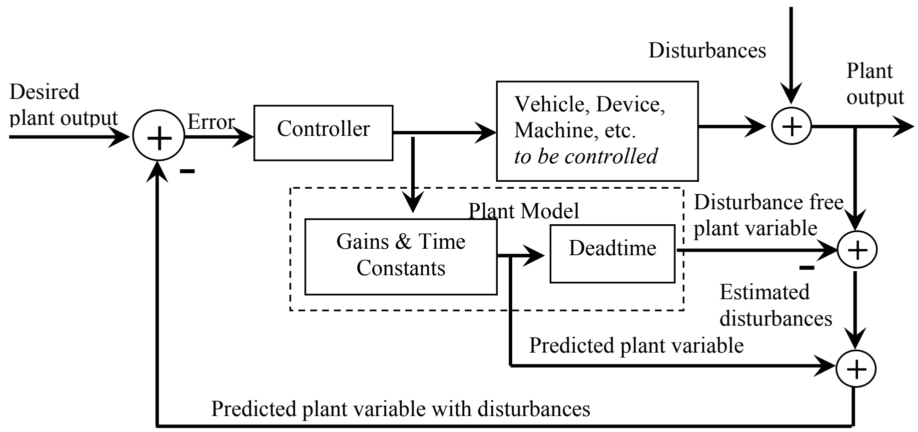

Figure 2: A forward model

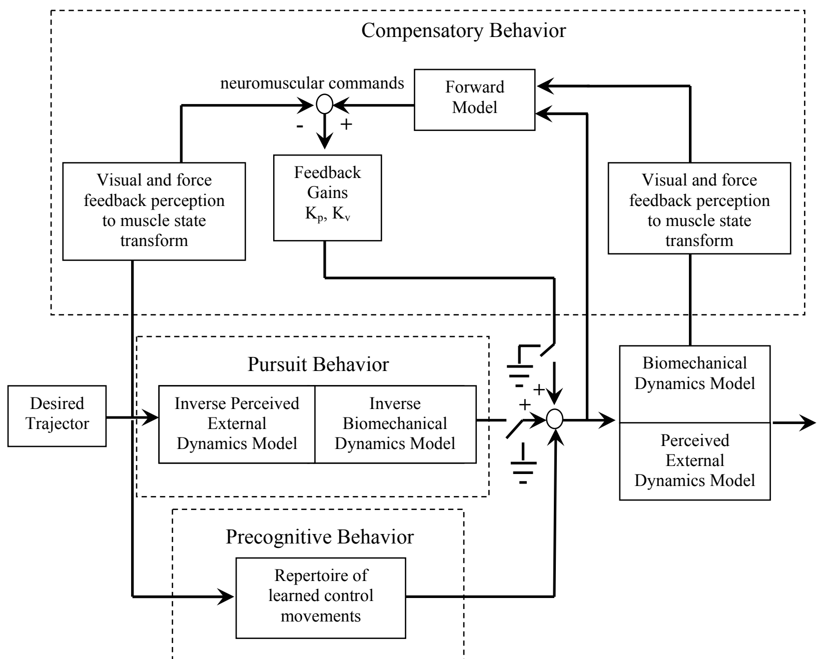

Figure 3: Control architecture for human arm trajectory tracking action.

2.2. Lateral Driver models

Many driver models have been proposed in the literature. The cross-over model [9,10] points out that the loop transfer function of a stable closed-loop system will exhibit a slope of -20 dB/decade around the cross-over frequency. This observed characteristic does not directly render an accurate driver model that can be implemented, but nevertheless can be used to guide driver model design and for sanity check of other models. Many of the earlier models rely on the compensatory action, and assume human behavior can be approximated by linear and time-invariant dynamics. These models are commonly referred to as transfer function models [11,12,13]. A more recent transfer function model is the STI (Systems Technology Incorporation) driver model [11]. This model uses road curvature along with vehicle lateral displacement as external inputs. The feedback cues include curvature error, lane position error, and yaw rate. It is commonly believed that the transfer function models are only good at describing human driver behavior under small perturbations.

Another group of models use a combined pursuit/compensatory action, and mimic human preview and predictive behavior by incorporating a forward model, and are known as the preview/predictive models [14]. In these models, the human drivers scan through future desired road path within a finite future distance when performing a driving task. This behavior is captured in the preview/predictive driver models. The term 'preview' refers to the driver's ability to see the future desired path and 'predictive' refers to the driver's ability to predict future vehicle response. Driver models that use preview information over a horizon often generate approximate inverse control actions, resulting in superior control quality when compared with transfer function models. This is especially true for high lateral acceleration path following tasks, e.g., sharp curves or double lane change maneuvers. One of the most well-known preview/predictive models is proposed by MacAdam [15], where the driver is assumed to behave like a preview optimal controller with delay. Since this model is one of the most verified models, and it is closely related to the model we are going to propose, the detail of this model is presented in the following. We would like to note that some transfer function driver models contain blocks, frequently with output derivatives to mimic driver's preview action [12]. Accurate prediction of driver steering under slowly increased curves was achieved. However, these models likely will not work under evasive maneuvers such as double lane changes.

MacAdam's model is based on the optimal preview control framework for single-input-single-output linear systems. Given the state equation (e.g., bicycle model) of a vehicle

$$\begin{aligned} \dot{x} &= Ax + Bu \\ y &= Cx \end{aligned} \tag{1}$$

the control (steering) signal minimizing a quadratic cost function is solved. The cost function proposed by MacAdam has the following form

$$u_{opt}(t) = \min_{u} \left\{ \int_{t}^{t+T_p} \left\{ \left[y_d(\eta) - y(\eta) \right]^2 \delta(\eta - t) \right\} d\eta \right\} \tag{2}$$

where $y_d(t)$ is the desired lateral displacement, $y(t)$ is the actual lateral displacement, and $\delta(t)>0$ is the weighting function over the preview window. In general, $u(t)$ could vary within the preview window $[t, t+T_p]$. However, the solution of this problem involves solving a partial differential equation and might be unnecessary for approximating human behavior. A simpler problem can be formulated by assuming $u(t+\tau) = u_{opt}(t), \forall\tau \in [0, T_p]$, which can be solved much more easily. The output of the linear dynamics Eq.(1) is decomposed into zero input response and zero state response,

$$y(t+\tau) = Ce^{A\tau}x(t) + C\left(\int_0^{\tau} e^{A\eta}d\eta\right)Bu(t) \equiv F(\tau)x(t) + G(\tau)u(t) \tag{3}$$

The optimal solution for Eq.(2) can then be obtained by substituting Eq.(3) into Eq.(2) and setting the partial derivative of the cost function J with respect to u to be zero,

$$u_{opt}(t) = \frac{\int_t^{t+T_p} \left\{\left[y_d(\eta) - F(\eta-t)x(t)\right]G(\eta)\delta(\eta-t)\right\} d\eta}{\int_t^{t+T_p} G(\eta)^2\delta(\eta-t)d\eta} \tag{4}$$

The optimal solution u_{opt}(t) shown above can be viewed as a "proportional feedback" controller operating on the error between the desired output and predicted zero-input output over the preview window $[t, t+T_p]$, rather than for a single point in time. This "previewed proportional control" was found to result in a control law that approximates average human driver behavior quite well and has been implemented in a commercial software [16].

Driver models developed over the last decade tend to be more comprehensive. Kiencke proposes a longitudinal and lateral driver model combining discrete event theory and classical control theory [17]. The purpose of the model is to develop a model structure that describes multiple human driver cognitive processes. The model proposed by Sharp et al. [18] uses the lateral displacement error over a preview horizon similar to the MacAdam's driver model plus an instantaneous yaw error feedback term. An independent speed control scheme is proposed, which involves specifying desired speed along the ideal vehicle path, and a simple inverse vehicle dynamics to calculate the necessary vehicle thrust. Prokop [19] combines the optimal preview control defined for various objectives (e.g., lane keeping, minimizing speed variation) with a PID tracking control law. Horiuchi et al. [20] suggests a multi-input driver model using lateral displacement and yaw errors in feedback form, each driver (controller) having different controller gains and delays. In an alternative approach by Gordon et al. [21], the driving behavior is decomposed into two sequential tasks: path planning, and feedback control. The path planning task in [21] is addressed through an infinite state representation of the desired path, in the form of a reference vector field. Simple proportional control law was then used when error to the planned path exists.

3. PROPOSED DRIVER MODEL

Even though many driver models exist in the literature, obviously it is impractical to expect any single driver model to capture all human sensory, cognitive and control behaviors. The selection of driver model thus depends on the scope of the simulation study. In this paper, we focus on the task of evaluating vehicle roll performance. In particular, the vehicles will be driven over well-defined closed-loop paths that have short time durations. The driver speed control behavior is ignored, and it is assumed that the vehicle simply coasts through these tests from a known entry speed. Due to the short duration of these tests, human adaptation (update of vehicle forward model) is assumed to be not occurring through the tests. The (internal) vehicle model used by the driver, however, will be obtained after long and rich driving excitations and is assumed to be an accurate linear approximation of the vehicle.

The adaptive predictive control (APC) framework is used as the underlying technique for the proposed model, incorporating three key components of humans' driving: use of preview information, off-line adaptation, and driving style in an optimal control setting.

Determining a proper preview time is an important decision to be made. A longer preview time leads to increased tracking error for human tracking tasks. A diminish in return is however observed, and it is known that roughly a preview time between 0.5 and 2 second is used by most human drivers.

Another important feature to be included is driving style. In many previous studies, human drivers were found to control the vehicle by using multiple cues, most dominantly the vehicle lateral displacement and yaw angle error. It is hypothesized that experienced drivers rely on yaw error more than inexperienced drivers to achieve better tracking performance while maintaining the same or higher level of damping. This is because an inexperienced driver tends to view the vehicle as a point mass, whereas a more experienced driver will be able to sense, and subsequently use vehicle yaw information to achieve better driving performance. Because this hypothesis has not been verified, in the remainder of this paper we will refer to these drivers to have different styles, rather than experience levels.

3.1. Mathematical Formulation

The nonlinear vehicle model is assumed to be

$$y = f(x,u) \tag{5}$$

where y is the vehicle lateral position, x is the vehicle state vector, and u is the steering angle. We assume the human driver behaves in an optimal fashion. The optimal steering action is determined by choosing the change in steering angle (Δu, from current steering) such that the following cost function is minimized:

$$\Delta u_{opt} = \min_{\Delta u} \left\{ J = \int_{t}^{t+T_p} \left[s(\eta) \right]^2 d\eta \right\} \tag{6}$$

where T_p is the preview horizon. The "sliding function" is defined as

$$s(\eta) = \left(\tau w_{\dot{y}}(\eta) \frac{d}{dt} + w_y(\eta) \right)^{n-1} y_{err}(\eta) \tag{7}$$

where

$$y_{err}(t) \equiv y(t) - y_d(t) \tag{8}$$

and y_d is the desired lateral position of the vehicle. It can be seen that $s(\eta)$ depends on three weighting parameters: τ, $1 \geq w_y(j) \geq 0$, and $1 \geq w_{\dot{y}}(j) \geq 0$. The constant '$n$' determines the number of derivative terms included in the sliding function. For the case when $n = 2$, Eq.(6) can be rewritten in the discrete-time format as,

$$\Delta u_{opt} = \min_{\Delta u} \left\{ J = \sum_{j=1}^{N} \left[w_y(j) y_{err}(t+jT) + \tau w_{\dot{y}}(j) \dot{y}_{err}(t+jT) \right]^2 \right\} \tag{9}$$

where the number of steps in the summation (N) is equal to preview time T_p over the step size (T). The desired trajectory 'y_d' is usually specified in the inertial coordinate system, but is transformed to the local (vehicle body) coordinate system 'y_d^*' to reflect the driver's viewpoint (Figure 4) [16]. Eq.(8) is modified to define the lateral position error in the local coordinate system,

$$y_{err}(t+jT) = y^*(t+jT) - y_d^*(t+jT) \tag{10}$$

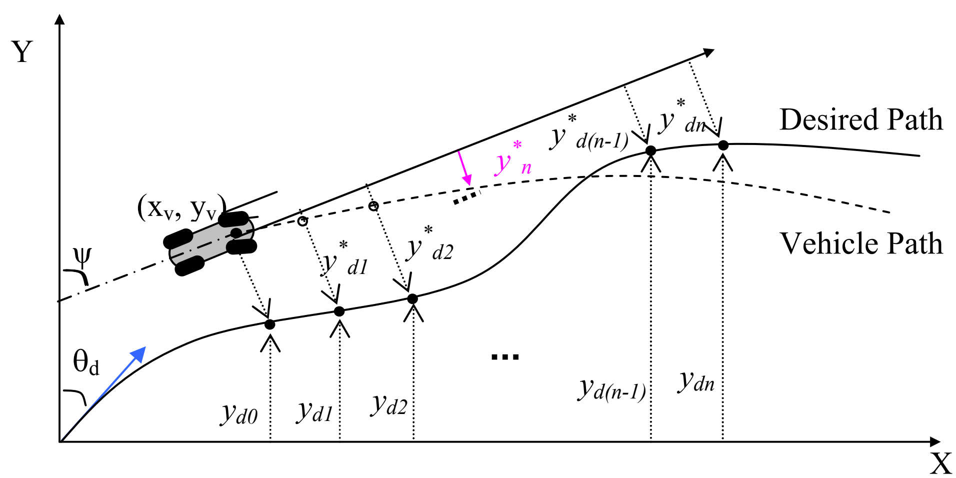

Figure 4: Inertial and vehicle body frames

The optimization problem defined above can be solved with 1 to N control steps. In other words, the steering angle can be assumed to be fixed at a constant level throughout the preview horizon, or can be changed as frequently as every simulation step. If we denote the number of discrete control steps allowed to be S_u, it is obvious larger S_u will result in better tracking performance. However, it is unrealistic to expect that the human drivers will change steering action more than 1-2 times over the preview horizon

(0.5 to 2 second). Therefore, a value S_u <=2 is usually used. In this case, the control signal stays constant through the first half of the preview horizon and change to another value for the second half. It is important to note that if $S_u = 1$ and $\tau = 0$, the APC structure presented above reduces to the MacAdam's driver model as a special case.

Further interpretations are possible by noting that the lateral displacement error rate can be rewritten as

$$\dot{y}_{err}(t) = \dot{y}(t) - \dot{y}_d(t) = v_y + v_x(\psi - \theta_d) \tag{11}$$

where v_y is the lateral speed, v_x is the longitudinal speed, ψ is the yaw angle of the vehicle, and θ_d is the tangent direction to the desired trajectory. The term $\psi - \theta_d$ thus represents vehicle yaw angle error. In many vehicle tests, the forward speed v_x is large, therefore the rate of change of vehicle lateral displacement is largely proportional to the vehicle yaw angle error. A driver with higher gain 'τ' (see Eq.(9)) more heavily penalizes $\dot{y}_{err}(t) = \dot{y}(t) - \dot{y}_d(t)$, i.e., pays more attention to vehicle's yaw plane motion. Extending this idea, higher order terms can be added to the cost function Eq.(9) to compensate for curvature error or even rate of change of curvature.

To find the optimal solution that minimizes the cost function given in Eq.(9), we write it in a vector form using the predictive control framework [23],

$$\begin{aligned} J = {} & [\boldsymbol{W}_y\boldsymbol{G}\Delta\boldsymbol{u} + \boldsymbol{W}_y\boldsymbol{F} + \boldsymbol{W}_{\dot{y}}\tau\frac{d}{dt}\left(\boldsymbol{G}\Delta\boldsymbol{u} + \boldsymbol{F}\right) - (\boldsymbol{W}_y\boldsymbol{y}_d + \boldsymbol{W}_{\dot{y}}\tau\dot{\boldsymbol{y}}_d)]^T \\ & [\boldsymbol{W}_y\boldsymbol{G}\Delta\boldsymbol{u} + \boldsymbol{W}_y\boldsymbol{F} + \boldsymbol{W}_{\dot{y}}\tau\frac{d}{dt}\left(\boldsymbol{G}\Delta\boldsymbol{u} + \boldsymbol{F}\right) - (\boldsymbol{W}_y\boldsymbol{y}_d + \boldsymbol{W}_{\dot{y}}\tau\dot{\boldsymbol{y}}_d)] \end{aligned} \tag{12}$$

where $\boldsymbol{W}_y = diag(\boldsymbol{w}_y)$ and $\boldsymbol{W}_{\dot{y}} = diag(\boldsymbol{w}_{\dot{y}})$, weighting matrices with nonzero elements on the diagonals, F and G are the state transition matrix and impulse response, as defined in Eq.(3). Eq.(12) can be re-written in a more compact form as,

$$J = [\widetilde{\boldsymbol{G}}\Delta\boldsymbol{u} + \widetilde{\boldsymbol{F}} - \widetilde{\boldsymbol{y}}_d]^T[\widetilde{\boldsymbol{G}}\Delta\boldsymbol{u} + \widetilde{\boldsymbol{F}} - \widetilde{\boldsymbol{y}}_d] \tag{13}$$

where $\widetilde{\boldsymbol{G}} = \boldsymbol{W}_y\boldsymbol{G} + \boldsymbol{W}_{\dot{y}}\tau\frac{d}{dt}\boldsymbol{G}$, $\widetilde{\boldsymbol{F}} = \boldsymbol{W}_y\boldsymbol{F} + \boldsymbol{W}_{\dot{y}}\tau\frac{d}{dt}\boldsymbol{F}$ and $\widetilde{\boldsymbol{y}}_d = \boldsymbol{W}_y\boldsymbol{y}_d + \boldsymbol{W}_{\dot{y}}\tau\dot{\boldsymbol{y}}_d$. Assuming the control signals are unbounded, the optimal solution that minimizes the quadratic cost function Eq.(13) is

$$\Delta\boldsymbol{u} = -\tilde{\boldsymbol{H}}^{-1}\boldsymbol{b} \tag{14}$$

where $\widetilde{\boldsymbol{H}} \equiv 2(\widetilde{\boldsymbol{G}}^T\widetilde{\boldsymbol{G}})$ and $\tilde{\boldsymbol{b}}^T \equiv 2(\tilde{\boldsymbol{F}} - \tilde{\boldsymbol{y}}_d)^T\tilde{\boldsymbol{G}}$. The inverse of $\tilde{\boldsymbol{H}}$ exists if the vehicle is controllable, a condition that is always true except when the vehicle forward speed is zero. If $S_u = 1$, all elements of vector $\Delta\boldsymbol{u}$ except the first are zero. The model parameters τ, w_y and $w_{\dot{y}}$ can be adjusted to fit different drivers. Clearly, τ represents the relative importance of yaw angle error compared with lateral displacement error. The weighting functions w_y and $w_{\dot{y}}$ indicate the relative importance of the lateral and yaw error terms and should decrease monotonically as time increases, so that distant future is weighted less and near future. In this paper, they are assumed to have the following form:

$$w_y(j) = \frac{\tanh[5(T_p/2 - t(j)) + \beta_y] + 1}{2} \tag{15}$$

$$w_{\dot{y}}(j) = \frac{\tanh[5(T_p/2 - t(j)) + \beta_{\dot{y}}] + 1}{2} \tag{16}$$

where $t(j) \in [t_o,\ t_o+T\ \ldots\ T_p-T,\ T_p]$ is the preview window. By adjusting β_y and $\beta_{\dot{y}}$, we defined three different preview windows--short, medium and long ($\beta_y, \beta_{\dot{y}}$=-1.0, 0.7 and 2.0 respectively). The effect of β_y and $\beta_{\dot{y}}$ on the weighting functions is shown in Figure 5. It can be seen that the tanh() function was used to achieve a smooth but rapid transition and ensures monotonicity. It is also important to point out that the weighting is almost constant (1 or 0) at the two ends of the preview window.

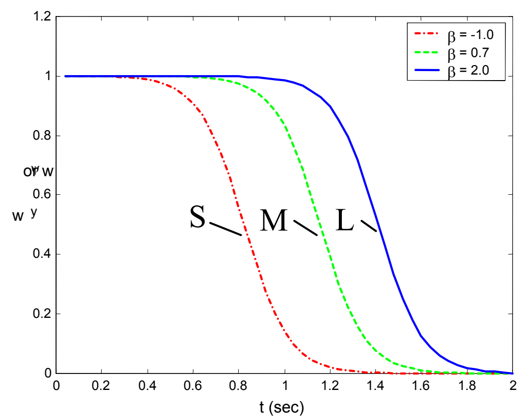

Figure 5: Weighting functions vs. time (short, medium and long)

3.2. Vehicle Model

The target vehicle studied in this paper is the 1998 Jeep Cherokee. The mathematical model is created using the TruckSim software produced by the Mechanical Simulation Corporation. Most of the vehicle parameters were obtained from a paper published by the Vehicle Research and Testing Center (VRTC) [23]. This TruckSim model was verified against VRTC test results [24] at 2 different vehicle speeds—25 and 50 mi/hr. The test maneuvers include right/left steer and brake, right/left turn (no braking), double lane change, pulse steering right/left, and ramp steering right/left. The steering input levels generate lateral acceleration as high as 0.6g.

The Trucksim model is used to generate all the "actual" vehicle response. In other words, it serves as the computation engine of the driving simulator, which generates all the data used to verify the proposed driver model. Since Trucksim contains many degrees of freedom and is computationally intensive, it is not suitable as an internal model for the virtual driver. We use an adaptive Controlled Auto-Regressive and Integrated Moving Average (CARIMA) model as the template for the internal model. The main advantage of using this model is that the model parameters are identified in an iterative fashion. This process is especially suitable if many vehicles need to be tested. For example, if NHTSA is to use the proposed driver model scheme to test rollover propensity of all new light ground vehicles, it will not be necessary to measure c.g. location, yaw moment of inertia, etc. for these vehicles. Instead, the measured vehicle response can be used to train the CARIMA model, which can be done much more quickly. The transfer function model also allows improved fit to the response from the nonlinear TRUCKSIM model, without being limited to, for example, the bicycle model format.

It is widely believed that human drivers learn to adapt to a vehicle gradually by learning to "invert the vehicle model". After a learning period, human drivers generally achieve good control accuracy, especially in terms of lane following. We assume this learning process is approximated by the least square optimization of a 4th order CARIMA model shown below

$$A(q^{-1})y(k) = B(q^{-1})q^{-d}u(k-1) + \frac{e(k)}{\Delta} \tag{17}$$

In this equation, $A(q^{-1})$ and $B(q^{-1})$ are both fourth-order polynomials of the z-domain operator q, $d=0$ and $\Delta \equiv 1-q^{-1}$. Both $A(q^{-1})$ and $B(q^{-1})$ are recursively identified to minimize the sum of square of the residual error $e(k)$.

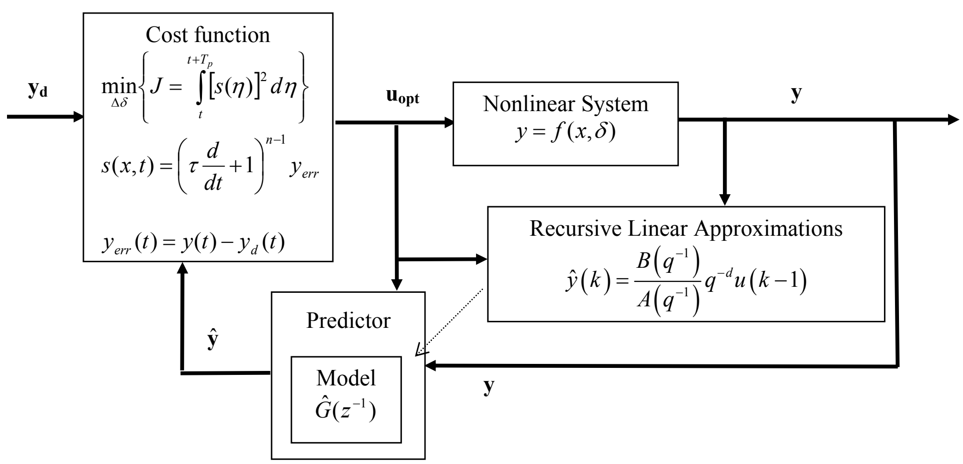

Figure 6: Proposed driver model structure

We ran the CARIMA model based on the steering ($u(k)$) and lateral displacement ($y(k)$) response from the TRUCKSIM model under selected rich steering excitations for an extended period of time. This training period stops when the model parameters ceased to change. The transfer function $\hat{G}(z^{-1}) \equiv B(z^{-1}) / A(z^{-1})$ is then convert to state space format and used as the predictive model, based on which vehicle response can be predicted and optimal steering can be calculated. Theoretically, the recursive least square update can continue to be turned on. In the remainder of this paper, however, we turn off the model adaptation because of the short duration of the driving tasks. The overall driver model used in this paper is summarized in Figure 6.

4. MODEL TUNING AND VALIDATION

In this section, the model structure proposed in the previous section will be verified. We first examine the effect of varying τ, w_y, $w_{\dot{y}}$, and S_u. These free parameters will then be adjusted to obtain driver models based on human-in-loop test data. The target driving maneuver is the German Alliance of Automotive Industry Moose Test (Figure 10). The vehicle is assumed to enter the test track at an initial speed of 85 km/hr, and the driver tries to follow the middle of the track, and stays within the restricted area delineated by the cones shown in Figure 7.

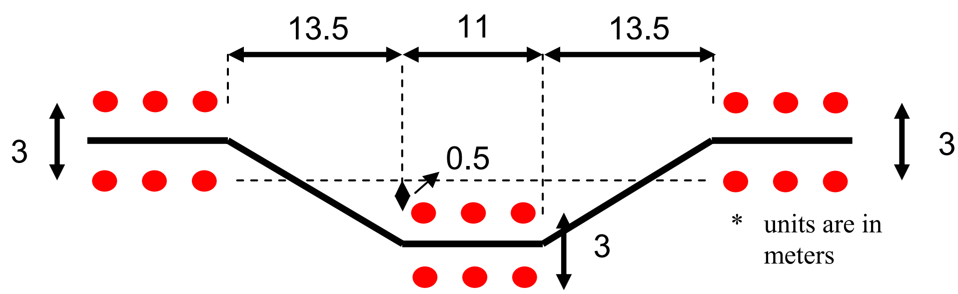

Figure 7: German Alliance of Automotive Industry (VDA) “Moose” Test

Lateral position of the vehicle c.g. and the steering wheel angle for three different weighting functions--short, medium, and long preview windows are plotted in Figure 8. For this case, no weighting on yaw angle error is used, i.e., the driver relies on vehicle lateral displacement for steering decision. As the driver spreads attention to a longer preview range, the tracking response becomes worse but the vehicle is obviously more stable. When the preview window is short, tracking error is best until the exit corner, when the vehicle lost grip and became unstable. The medium preview case provides a better trade-off between tracking performance and stability, but the result is still not satisfactory.

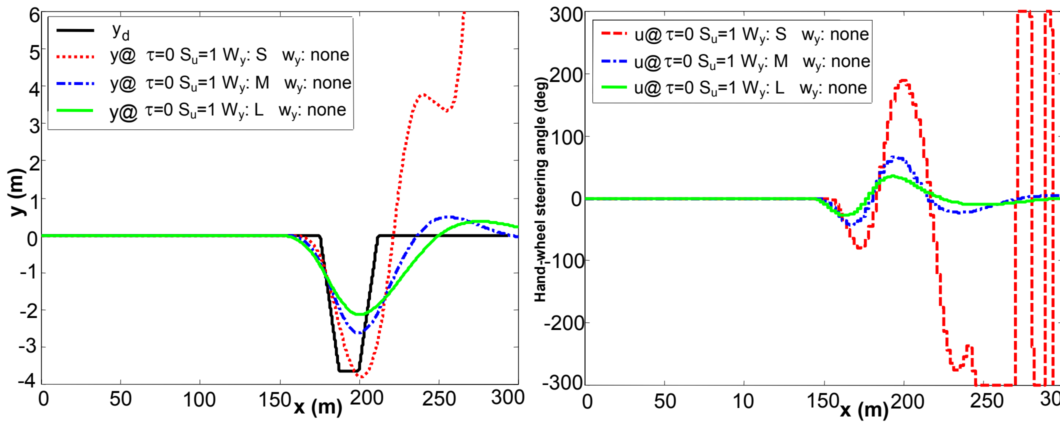

Figure 8: Vehicle performance for three different weighting functions

When the yaw angle error is used in the cost function, i.e., $\tau \neq 0$, the driver performance is significantly improved. Even when the short preview window is used, the driver can steer the vehicle back to the desired trajectory (Figure 9). In the meantime, the tracking performance was significantly improved to the previous (the "MacAdam" case).

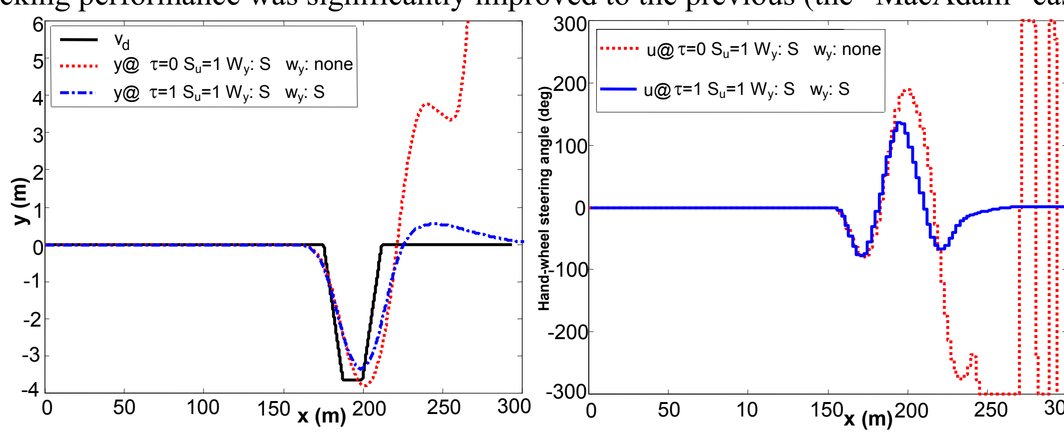

Figure 9: Vehicle performance for lateral only and lateral and yaw preview

As discussed before, the optimal driver action can be solved assuming that the driver steering angle is kept constant throughout the preview window (S_u=1) or changed once (S_u=2). When S_u is increased from 1 to 2, improved tracking performance is observed, especially for the medium and long preview cases (Figure 10). The effect of increased S_u was found to be similar to reduced preview window.

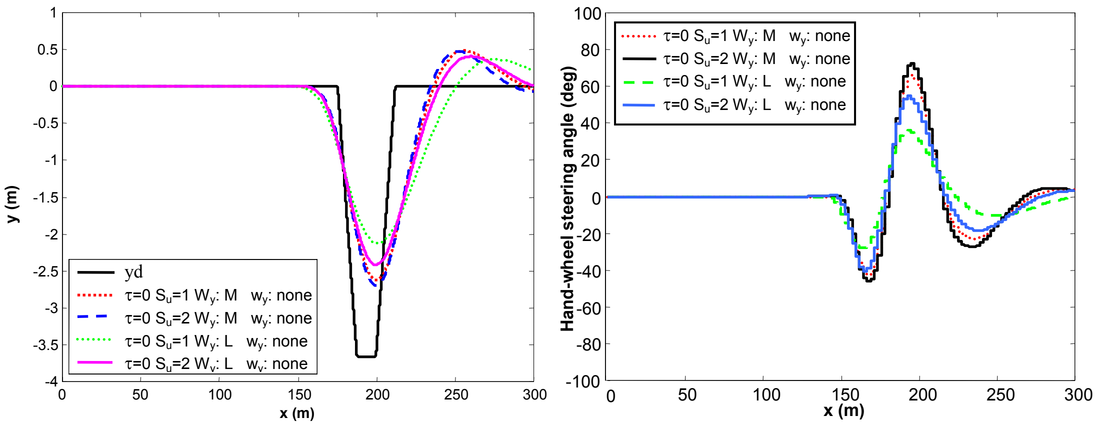

Figure 10: Vehicle response under different S_u

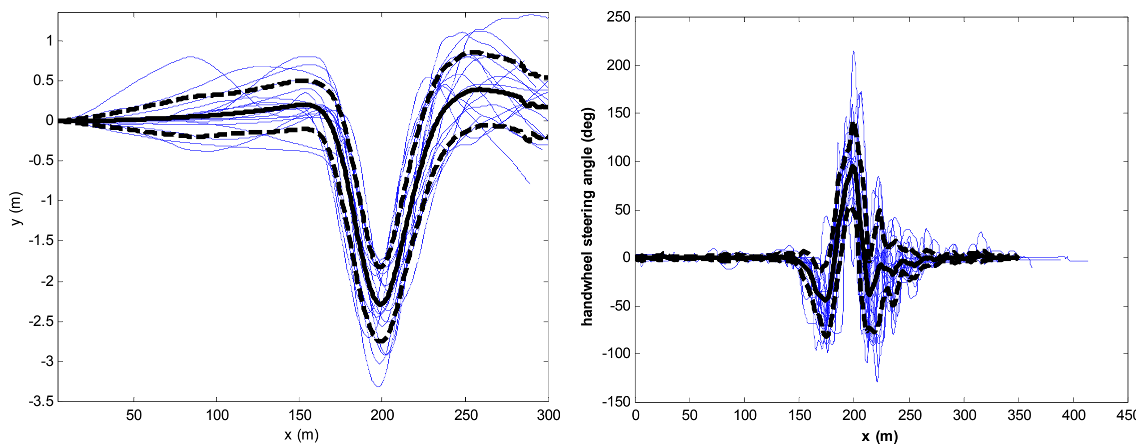

Figure 11: Human driver responses obtained from driving simulator tests

Experimental data taken from 22 human drivers on a driving simulator [26] are then analyzed. Actual steering and vehicle response, together with three time traces—constructed from the mean, and mean ± one standard deviation (σ) of the 22 real human drivers are given in Figure 11. It can be seen that the behavior of actual human drivers span a very wide range. We decided not to fit the behavior of individual drivers. Rather, the proposed model template is tuned to span the range between mean+σ and mean-σ. Because the range of steering inputs is from 22 real drivers, they are statistical representation of real driver behaviors. By varying the two weighting functions β_y and β_ψ as well as τ, we successfully approximated the hand-wheel steering angle as shown in Figure 12. The model predicted steering stays close to test results except around the last corner. We postulate that this is because many of the drivers used in the driving simulator had difficulty stabilizing the simulated vehicle. Around the last corner, the simulated vehicle yaws a lot more than what were typically seen on a real test track, perhaps due to the fact the simulated vehicle is harder to control than a real vehicle. The oscillations in steering angle can be seen from all three "virtual test drivers" but not from our models. We found that the "smooth" driver, who produces least steering (and largest tracking error), relies on vehicle lateral motion. This is also the only driver that uses a long preview window on lateral displacement. On the contrary, an "aggressive" driver follows the test track the closest, generates the largest steering, and uses vehicle yaw feedback signal the most (with the largest value for τ).

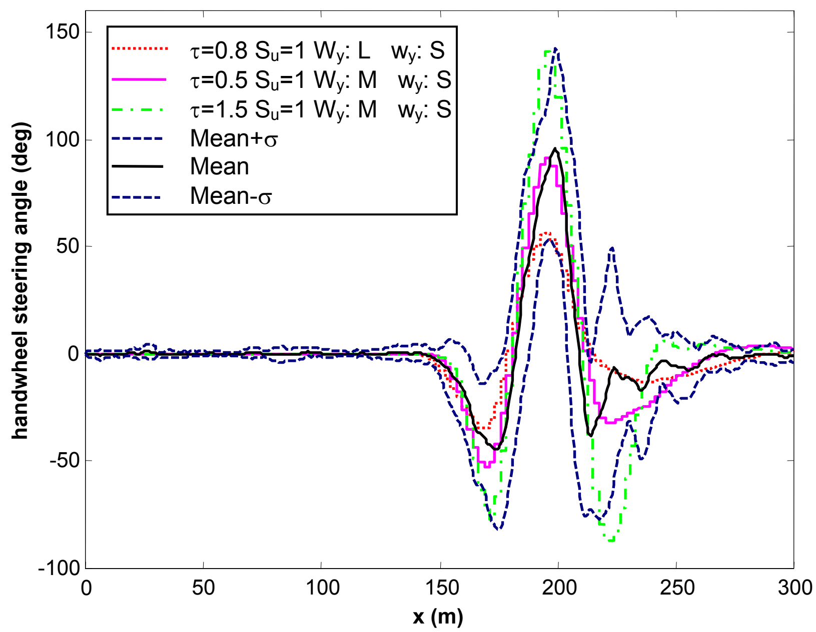

Figure 12: Mean, mean ± standard deviation of handwheel steering angle profiles for the actual drivers and driver model handwheel steering angle profiles

5. CONCLUSION

In this paper, a flexible lateral driver model in an adaptive predictive control framework is presented. The driver behavior is approximated by an optimal algorithm minimizing a performance cost function over a preview window. The cost function includes penalty terms on yaw error as well as lateral position error. The driver is assumed to obtain a good internal model of the vehicle recursively, which is then used to calculate vehicle response in the preview horizon.

The proposed driver model solves a cost function similar to the one used in the MacAdam's driver model. However, there are three major differences. First, unlike MacAdam's driver model, higher derivatives of lateral position error (yaw angle error, curvature error, etc.) could be included in the cost function to give additional flexibility to represent different driver behaviors. Secondly, the internal model can be updated recursively to capture human adaptation and learning to new vehicles. Finally, the human steering input is not constrained to stay constant within the preview horizon. Overall, the proposed method can be described as a generalized version of the MacAdam's driver model. The added model parameters were found to be quite beneficial. Simulation results show that the driver model can be adjusted to represent a range of drivers with different characteristics, thus allowing human-in-loop simulation assessment of active safety systems.

The proposed driver model stays at fairly low level in the overall driving task—we did not discuss any issues related to human cognition and trajectory planning. Rather, the desired path is assumed to be given (e.g., from a higher level module in the overall, integrated driver model). The integration of this proposed model into a more comprehensive driving model will be an interesting future task.

REFERENCES

1. Traffic Safety Facts 2000, National Highway Traffic Safety Administration, 2001.
2. Hendricks, D.L., Fell J.C. and Freedman M.: The relative frequency of unsafe driving acts in serious traffic crashes. Report no: DOT-HS-809-206, Jan 2001.
3. Davidson, P.R., Jones, R.D., Sirisena, H.R**.** and Andreae, J.H.:Evidence for the Formation of Internal Inverse Models in the Human Motor System. *Human Movement Science*, Vol. 19, pp. 761-795, 2000.
4. Miall, R.C., Weir, D. J. ; Wolpert, D. M. and Stein, J. F.: Is the Cerebellum a Smith Predictor?, *Journal of Motor Behavior*, Vol 25, No.3, pp 203-216, 1993.
5. Bhushan, N. and Shadmehr, R.: Computational nature of human adaptive control during learning of reaching movements in force fields. *Biological Cybernetics*, No 81, pp 39-60, 1999.
6. Haruno M., Wolpert D., and Kawato M.: Multiple paired forward-inverse models for human motor learning and control. *Advances in Neural Information Processing Systems,* MIT Press, Cambridge, Massachusetts, pp.31-37,1999.
7. Miall R.C. and Wolpert D.M.: *Forward models for physiological motor control. Neural Networks*, Elsevier Science Ltd., Vol. 9, No.8, pp 1265-1279, 1996.
8. Wolpert D. M. and Ghahramani Z.: Computational principles of movement neuroscience. Nature Neuroscience Supplement, Vol. 3, Nov., 2000, pp.1212-1217.
9. McRuer, D.T.: Human Dynamics in Man Machine Systems. *Automatica*, Vol. 16, No.3,1980, pp.237-253.
10. Ashkenas, I.L. and McRuer, D.T.: A theory of handling qualities derived from pilot/vehicle system consideration, Aerospace Engineering, No.2, 1962, pp.83-102.
11. Allen,R.W., Rosenthal, T.J and Szostak H.T.: Analytical Modeling of driver response in crash avoidance maneuvering –Volume 1: Technical Background. NHTSA, DOT HS 807 270, April, 1988.

12. Hess, R.A. and Modjtahedzadeh, A.:A control theoretic model of driver steering behavior. *IEEE Control Systems Magazine*, Vol.10, issue 5, August 1990, pp 3-8.
13. Ornstein, G.N.: The Automatic Analog Determination of Human Transfer Function Coefficients. Med. Electron. Bio. Eng. 1 (3) (1963).
14. MacAdam, C.C.: Application of an Optimal Preview Control for Simulation of Closed-Loop Automobile Driving. *IEEE Transactions on Systems, Man, and Cybernetics*, Vol 11, No. 6, June, 1981, pp.393-399.
15. MacAdam, C.C.: An Optimal Preview Control For Linear Systems. *Transactions of ASME*, Vol. 102, September, 1980, pp.188-190.
16. Trucksim Manual, http://www.carsim.com/downloads/pdf/ts5_user.pdf.
17. Kiencke, U., Majjad R., and Kramer, S.: Modeling and performance analysis of a hybrid driver model. *Control Engineering Practice* 7,pp 985-991,1999.
18. Sharp, R.S., Casanova D., and Symonds, P.: A mathematical model for driver steering control, with design, tuning and performance results. *Vehicle System Dynamics*, Vol. 33, pp 289-326, 2000.
19. Prokop, G.: Modeling Human Vehicle Driving by Model Predictive Online Optimization. *Vehicle System Dynamics*, Vol. 35, No. 1, pp. 19-53, 2001.
20. Horiuchi, S, and Yuhara, N.: An analytical approach to the prediction of handling qualities of vehicles with advanced steering control system using multi-input driver model. *Transactions of ASME*, Vol.122, pp 490-497, 2000.
21. Gordon, T.J., Best, M.C., and Dixon P.J.: An automated driver based on convergent vector fields. Proc. Instn Mech Engrs, Vol. 216, Part D, J. Automobile Engineering, pp 329-347, 2002.
22. Camacho,E.F. and Bordons,C., *Model Predictive Control in the Process Industry*, Springer-Verlag,1995.
23. Salaani, M.K., Guenther, D.A. and Heydinger, G.J.: Vehicle Dynamics Modeling for the National Advanced Driving Simulator of a 1997 Jeep Cherokee. SAE Paper No. 1999-01-0121,
24. Chen, B. and Peng, H.: A Rollover Warning Algorithm for Sports Utility Vehicles. Proceedings of the 1999 American Control Conference, San Diego, CA.
25. Chen, B. and Peng, H.: Differential-Braking-Based Rollover Prevention for Sport Utility Vehicles with Human-in-the-loop Evaluations. *Vehicle System Dynamics*, Vol.36, No.4-5, pp.359-389, November, 2001