

Optimal Direct Yaw Controller Design for Vehicle Systems with Human Driver

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ABSTRACT

Dynamic game theory brings together different features that are keys to many situations in control design: optimization behavior, the presence of multiple agents/players, enduring consequences of decisions and robustness with respect to variability in the environment, etc. In the presented methodology, vehicle stability is represented by a cooperative dynamic/difference game such that its two agents (players), namely, the driver and the direct yaw controller (DYC), are working together to provide more stability to the vehicle system. While the driver provides the steering wheel control, the DYC control algorithm is obtained by the Nash game theory to ensure optimal performance as well as robustness to disturbances. The common two-degree of freedom (DOF) vehicle handling performance model is put into discrete form to develop the game equations of motion. To evaluate the developed control algorithm, CarSim with its built-in nonlinear vehicle model along with the Pacejka tire model is used. The control algorithm is evaluated for a lane change maneuver, and the optimal set of steering angle and corrective yaw moment is calculated and fed to the test vehicle. Simulation results show that the optimal preview control algorithm can significantly reduce lateral velocity, yaw rate, and roll angle, which all contribute to enhancing vehicle stability.

INTRODUCTION

Stability in a vehicle system is determined by the total performance of all dynamics subsystems. Among different subsystems, vehicle driver and vehicle stability control systems share the most significant responsibility in providing stability in severe handling maneuvers. A rational driver tends to keep the vehicle stable throughout the maneuver; however, due to unexpected or uncontrolled events, vehicle stability is jeopardized and the driver is unable to control the vehicle. It is in these scenarios that vehicle stability control (VSC) system plays a crucial role in stabilizing the vehicle.

Vehicle active safety systems are designed to improve driving safety while the driver is still in control of the vehicle. The advancement of new VSC systems that can augment the driver input necessitates a better understanding of how the vehicle and driver can co-exist in a manner that are complementary, not contradictory. The literature concerned with the interaction modeling of the vehicle driver and control system are classified in two categories.

In the first and the most popular category, the vehicle driver and the vehicle stability controller are two independent subsystems of the vehicle in which the performance and strategy of each system does not significantly affect the performance and strategy of the other system. For example, most existing driver models ignore the fact that human drivers respond differently as the vehicle control system is changed [1,2], or most vehicle control literature has reported

control designs that assume a predetermined steering input, and thus, ignoring the driver's transient response to the current event [3,4].

The second category includes researches that consider vehicle stability as collaboration between driver and the vehicle stability control system. Wenzel showed that considering a joint combination of a driver model and active front steering control may result in improved vehicle stability and performance [5]. Regardless of the complexity, cooperative control of the driver's input and vehicle control system control actions trivially results in globally optimal solution to vehicle stability problems.

For vehicle directional control, the steering wheel is the primary means for control actuation. Many driver models try to approximate the real driver's road tracking performance, assuming certain driver inputs and outputs. If the controller is aware of the driver's intentions, the driver mathematical model can be traced back iteratively to determine its significant factors. Accordingly, establishing a technique for detecting the driver's intentions or for recognizing driver model has been a challenging problem for vehicle system researchers. Kuge [6] developed a driver behavior recognition method based on hidden Markov models to characterize and detect driving maneuvers and place it in the framework of a cognitive model of human behavior. In another research by McCall and his colleagues [7], driver's behavior and the lane change intent is analyzed using robust sparse Bayesian learning methodology and it is shown that by incorporating a state-of-the-art Sparse Bayesian Learning classifier with well-motivated evaluation metrics, the likelihood of driver intent inference system algorithmic failure reduces.

In this paper, a novel optimal driver-controller interaction strategy is developed based on linear quadratic Game Theory. The model includes the driver's directional control through introducing steering wheel angle and the vehicle direct yaw control (DYC) system through imposing a corrective yaw moment using differential braking of the four wheels. As a result, it is shown that globally optimal performance is obtained in the case that the effects of driver's decision making on the controller and vice versa are taken into account and the interactions are correctly modeled.

VEHICLE MODELS

The simulation software CarSim by Mechanical Simulation [8] is used in numerical simulations to analyze the response of the controlled vehicle. Its built-in model include nonlinear tire models according to combined sideslip theory [9], nonlinear spring model, nonlinear front steering system, and incorporates the major kinematics and compliance effects in the suspension and steering systems including differential load transfer for each wheel.

CONTROL MODEL

However, to design the controller, a widely used simplified linear single track vehicle model is considered which captures the essential vehicle steering dynamics [10]. In this respect, the tire forces are assumed to be linear functions of tire slip angle. This model captures the needed dynamic information for yaw as well as lateral degrees of freedom. In order to derive the equations, it is assumed that vehicle motion is represented by its global lateral position and velocity, and the yaw angle and yaw rate at the vehicle center of mass. The state variable vector becomes

$$x = (y \quad \dot{y} \quad \psi \quad \dot{\psi})^T \quad (1)$$

where, y is the global lateral position of the vehicle CG, $\dot{y}$ is the global lateral velocity in Y direction with respect to a fixed ground coordinate, and ψ , $\dot{\psi}$ are yaw angle and yaw rate, respectively.

For the sake of simplicity, the mathematical model is linearized around the operating conditions

$$x^* = 0_{4 \times 1}, \delta_{SW}^* = 0, M_{zc}^* = 0$$

Thus, the equation of motion for a constant forward speed is given by:

$$\dot{x}_c(t) = A_c x_c(t) + B_{1c} \delta_{SW}(t) + B_{2c} M_{zc}(t) \quad (2)$$

with

$$A_c = \begin{bmatrix} 0 & 1 & v_x & 0 \\ 0 & -\frac{C_{\alpha F} + C_{\alpha B}}{m v_x} & 0 & -v_x - \frac{l_F C_{\alpha F} - l_B C_{\alpha B}}{m v_x} \\ 0 & 0 & 0 & 1 \\ 0 & \frac{l_F C_{\alpha F} - l_B C_{\alpha B}}{I_z v_x} & 0 & -\frac{l_F^2 C_{\alpha F} + l_B^2 C_{\alpha B}}{I_z v_x} \end{bmatrix}$$

$$B_{1c} = \begin{bmatrix} 0 & \frac{C_{\alpha F}}{r_{st} m} & 0 & \frac{l_F C_{\alpha F}}{r_{st} I_z} \end{bmatrix}^T, \quad B_{2c} = \begin{bmatrix} 0 & 0 & 0 & \frac{1}{I_z} \end{bmatrix}^T$$

where u_1 is the steering wheel angle (δ_{SW}), u_2 is the compensated yaw moment (M_{zc}), and $C_{\alpha F}$, $C_{\alpha B}$ denote the front and rear tire cornering stiffness, respectively, relating linear tire forces to their corresponding linear sideslip angles.

The relevant linear vehicle model is translated to the discrete-time difference equation as,

$$x_d \{k+1\} = A_d x_d \{k\} + B_{1d} u \{k\} + B_{2d} u \{k\} \quad (3)$$

where A_d , B_{1d} , B_{2d} are obtained from the discrete bilinear transformation of the corresponding continuous-time matrices of A_c , B_{1c} , B_{2c} .

PREVIEW MODEL

The idea of a multi-point preview model of path-following steering control used by Sharp et al. originates from linear discrete-time preview control of active suspension [1]. The inputs to the model are effectively the previewed path error and the lateral and yaw velocities of the vehicle, and the output of the model is the steering angle. Applying optimization theory he showed that the feedback gains depended on the weights applied to path and heading errors and steering control action, and that the preview gains reflect the vehicle dynamics.

The relevant linear vehicle model is translated to the discrete-time form of Eq. (3), and the lateral profile of the road is considered in discrete sample value form, with sample values from past observations of the road ahead being stored as states of the full vehicle/road system. As the system moves forward in time, a new road sample value is read in and the oldest stored value is discarded, corresponding to the vehicle having passed the point on the road to which this oldest value refers. All the other road sample values are shifted through the time step, nearer to the vehicle. The dynamics of this shift register process are represented mathematically by

$$y_r\{k+1\} = A_r y_r\{k\} + B_r y_{ri}\{k\} \quad (4)$$

where A_r and B_r are of the form

$$A_r = \begin{bmatrix} 0 & 1 & 0 & \dots & \dots & 0 \\ 0 & 0 & 1 & \dots & \dots & 0 \\ 0 & 0 & 0 & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & 0 & \dots & 0 \end{bmatrix}, \quad B_r = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \dots \\ 1 \end{bmatrix}$$

Combining vehicle and road equations together, we obtain the full dynamic system description

$$\begin{bmatrix} x_d\{k+1\} \\ y_r\{k+1\} \end{bmatrix} = \begin{bmatrix} A_d & 0 \\ 0 & A_r \end{bmatrix} \begin{bmatrix} x_d\{k\} \\ y_r\{k\} \end{bmatrix} + \begin{bmatrix} B_{1d} \\ 0 \end{bmatrix} \delta_{SW}\{k\} + \begin{bmatrix} B_{2d} \\ 0 \end{bmatrix} M_{zc}\{k\} + \begin{bmatrix} 0 \\ B_r \end{bmatrix} y_{ri}\{k\} \quad (5)$$

The complete problem is now in a standard form,

$$z\{k+1\} = Az\{k\} + B_1 u_1\{k\} + B_2 u_2\{k\} + E y_{ri}\{k\} \quad (6)$$

where $u_1 = \delta_{SW}$ is the discrete-time steering wheel angle signal, and $u_2 = M_{zc}$ is the discrete corrective yaw moment around the vehicle center of mass.

If the reference sample y_{ri} is a white-noise sample from a random sequence, the state-preview system of Eq. (3) is

controllable if the state system of Eq. (2) is controllable, i.e., if (A_c, B_c) is controllable.

CONTROL ALGORITHM DESIGN

Consider the discrete-time infinite linear quadratic difference game with 2 players as formed in Eq. (6), and each player $i = 1, 2$ has a control function $u_i = (\delta_{SW}, M_{zc})$ at his disposal which is dynamically coupled by a system of difference rewritten as,

$$z^+ = Az + B_1 u_1 + B_2 u_2 \quad (7)$$

where the time step, k , is omitted for the sake of simplicity, and the white-noise reference signal y_{ri} is neglected in the difference game.

For every player $i = 1, 2$, a quadratic cost function is defined as

$$\phi_i = \frac{1}{2} \sum_{k=0}^{\infty} L_i = \frac{1}{2} \sum_{k=0}^{\infty} \left(z^T Q_i z + \sum_{j=1}^2 u_j^T R_{ij} u_j \right) \quad (8)$$

where all weighting matrices are constant, Q_i is symmetric, $R_{ii} > 0$.

NASH SOLUTION TO LQ DIFFERENCE GAMES

The Nash equilibrium is defined such that it has the property that there is no incentive for any unilateral deviation by any one of the players [11,12,13]. In the other words, at Nash equilibrium with u_i^* , the player who chooses to change his/her strategy cannot improve his/her payoff. Therefore, the Nash equilibrium is constituted by the N-tuple of strategies u_i^* if the following inequalities are satisfied for all admissible strategies:

$$\begin{cases} \phi_1^* \square \phi_1(u_1, u_2^*) \geq \phi_1(u_1^*, u_2^*) \\ \phi_2^* \square \phi_2(u_1^*, u_2) \geq \phi_2(u_1^*, u_2^*) \end{cases} \quad (9)$$

The optimal control [14] is obtained as

$$u_i^* = -R_{ii}^{-1} B_i^T P_i^+ z^+, \quad i = 1, 2 \quad (10)$$

Restricting the controller to the linear feedback control approach, the optimal solution becomes,

$$u_i^* = -R_{ii}^{-1} B_i^T P_i^+ z^+, \quad i = 1, 2$$