

Optimal Torque Control for an Electric-Drive Vehicle with In-Wheel Motors: Implementation and Experiments

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ABSTRACT

This paper presents the implementation of an off-line optimized torque vectoring controller on an electric-drive vehicle with four in-wheel motors for driver assistance and handling performance enhancement. The controller takes vehicle longitudinal, lateral, and yaw acceleration signals as feedback using the concept of state-derivative feedback control. The objective of the controller is to optimally control the vehicle motion according to the driver commands. Reference signals are first calculated using a driver command interpreter to accurately interpret what the driver intends for the vehicle motion. The controller then adjusts the braking/throttle outputs based on discrepancy between the vehicle response and the interpreter command. A test vehicle equipped with four in-wheel electric motors, vehicle sensors, communication buses, and dSPACE rapid prototyping hardware is instrumented and the control performance is verified through vehicle handling tests under different driving conditions.

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INTRODUCTION

Increasing environmental and safety concerns, along with rising gasoline prices, are driving a worldwide shift in the automotive industry towards the development of green intelligent transportation systems. Today, electric vehicles (EVs) are seen as the leading contender to displace existing fleets of gasoline-powered cars. EVs allow for the possibility of zero greenhouse-gas and air-pollutant emissions as well as very little noise pollution. Another important advantage of electric vehicles over the conventional internal combustion engines (ICEs) is the very high energy efficiency and relatively low cost of the electric motor. The main concern currently being faced is the low energy and power densities of batteries compared to the liquid fuels.

EVs use electric motors to propel the car and use batteries to store electricity. Four in-wheel motors, two independent

motors for the front and rear axles, and a single motor running all four wheels are possible motor configurations for shaping the propel system. The rapid dynamics of the motors provide the opportunity to accurately control the wheel speeds, thereby achieving better handling performance. In addition, this property allows stability and safety controllers such as active cruise control, collision avoidance, and emergency brake assist to apply their commands much faster, resulting in better incident prevention. Motors in EVs also help in stabilizing vehicle motion by generating counter-directional torques between the left and right wheels using control strategies such as active software differentials, active brake bias, and brake steer. While applying these controllers on ICEVs requires sophisticated hardware components that add complexity to the vehicle structure, the application of such controllers in EVs can be carried out using only software modification.

Substantial research has been carried out on the development of electric vehicles and related control strategies during the last two decades. For example, Ref. [1] provides an overview of electric-vehicle technology while Refs. [2] and [3] report on the application of different stability controllers in electric vehicles. Moreover, a combination of direct yaw-moment and active front steering controllers for electric vehicles with four in-wheel motors is proposed as a stability control system in Ref [4]. A torque-control distribution for an electric vehicle is presented in Ref [5] that takes advantage of front-wheel drive, rear-wheel drive, and all-wheel drive configurations in vehicles. The applications of electric braking control systems and traction control systems in electric vehicles are presented in Refs. [6] and [7], respectively, while Ref. [8] presents a nonlinear optimal theory used for controlling the speed of light-weighted all-electric vehicles. Refs. [9] to [10] discuss the effectiveness of their proposed direct yaw moment control strategies on stability enhancement in electric vehicles.

Despite the existence of research on stability control in electric vehicles, it is still an open research subject. This paper proposes a controller that is formulated using a solution of an off-line optimization problem, and takes feedback from the acceleration signals instead of the velocity signals. Since the control actions are optimized off-line, the controller is highly computationally efficient. The proposed controller is developed such that the actual vehicle's motion is adjusted according to driver commands. Thus, it is necessary to accurately interpret how the driver intends to manipulate the vehicle's motion, so as to enable the controller to generate appropriate control actions. For this purpose, a driver command interpreter module was developed. The efficiency of the controller for vehicle handling and the effects of hardware communications on overall system performance are shown through experiments carried out by driving the car based on standard maneuvers. The details of the work are given in the following sections.

CONTROL FORMULATION

The dynamics of a vehicle is consequence of forces and moment acting on the center of gravity (C. G.) of a vehicle. It is known that the C.G. forces are direct resultants of the tire forces, adjusted by a driver through steering and gas/brake pedal. However, it is possible that the vehicle motion differs from what the driver intended due to different reasons such as insufficient contact between road and tire or excessive lateral acceleration. Thus, the objective of the proposed controller is to keep the vehicle on the driver's intended directional motion while providing the driver with a normal driving experience.

Defining the desired C.G. forces as those generated in stable conditions, the discrepancy between the desired C.G. forces and the actual ones can be corrected by controlling tire forces. Hence, the proposed control methodology uses longitudinal tire forces as the control variables.

The C.G. force errors and longitudinal tire force vectors are defined as:

$$E = [F_x^* - F_x, F_y^* - F_y, G_z^* - G_z]^T = [E_x, E_y, E_z]^T \quad (1)$$

$$f = [f_{x1}, f_{x2}, f_{x3}, f_{x4}]^T \quad (2)$$

Definitions of parameters are provided at the end of this paper. With neglecting variation of lateral tire forces due to lack of active steering system, the error between the desired C.G. forces and actual ones can be adjusted as follows:

$$F_x^* - F_x(f + \delta f) \cong F_x^* - \left[F_x(f) + \frac{dF_x(f)}{df} \delta f \right] = E_x - \frac{dF_x(f)}{df} \delta f \quad (3)$$

$$F_y^* - F_y(f + \delta f) \cong F_y^* - \left[F_y(f) + \frac{dF_y(f)}{df} \delta f \right] = E_y - \frac{dF_y(f)}{df} \delta f \quad (4)$$

$$G_z^* - G_z(f + \delta f) \cong G_z^* - \left[G_z(f) + \frac{dG_z(f)}{df} \delta f \right] = E_z - \frac{dG_z(f)}{df} \delta f \quad (5)$$

where, δf is the vector of longitudinal tire force adjustment calculated by the control unit.

The following objective function to be minimized includes the weighted combination of error between actual and desired vehicle C.G. forces and control action:

$$P = \frac{1}{2} [(E - A_F \delta f)^T W_E (E - A_F \delta f) + \delta f^T W_{df} \delta f] \quad (6)$$

where, W_E and W_{df} are the semi-positive definite diagonal weight matrices on the C.G. force error and control action vectors, respectively, and A_F is associated with vehicle configuration where for a four wheel drive vehicle is:

$$A_F = \begin{bmatrix} \frac{dF_x(f)}{df} \\ \frac{dF_y(f)}{df} \\ \frac{dG_z(f)}{df} \end{bmatrix} = \begin{bmatrix} \frac{\partial F_x}{\partial f_{x1}} & \frac{\partial F_x}{\partial f_{x2}} & \frac{\partial F_x}{\partial f_{x3}} & \frac{\partial F_x}{\partial f_{x4}} \\ \frac{\partial F_y}{\partial f_{x1}} & \frac{\partial F_y}{\partial f_{x2}} & \frac{\partial F_y}{\partial f_{x3}} & \frac{\partial F_y}{\partial f_{x4}} \\ \frac{\partial G_z}{\partial f_{x1}} & \frac{\partial G_z}{\partial f_{x2}} & \frac{\partial G_z}{\partial f_{x3}} & \frac{\partial G_z}{\partial f_{x4}} \end{bmatrix} \quad (7)$$

Since W_E and W_{df} are semi-positive definite, the quadratic objective function (6) is positive definite as well. Thus, the condition for minimization of P as a linear set of equations in the matrix form is:

$$\frac{\partial P}{\partial \delta f} = 0 \quad (8)$$

The minimizing of the objective function P results in:

$$\delta f = [W_{df} + (A_F^T W_E) A_F]^{-1} (A_F^T W_E) E \quad (9)$$

Thus, the torque required to be added to the nominal torque provided by the driver is:

$$\delta Q = \delta f \cdot R_t \quad (10)$$

The proposed controller has a closed-form solution for an off-line optimization problem thereby making its real-time implementation more effective than model-based controllers available in the literature. In addition, the controller feedbacks are acceleration signals instead of velocities. In practice, the acceleration signals may be measured accurately by accelerometers or Inertial Measurement Units (IMU). Since the controller takes feedback from acceleration instead of velocities, its performance can be studied through the concept of state-derivative feedback systems. For brevity of the paper, more details about the control structure, the stability of the closed loop system, and controller gain optimization are referred to [11]. Figure 1 represents the overall block diagram of the closed-loop control system.

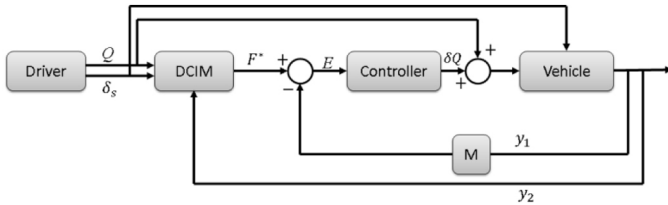


Figure 1. Block diagram of the overall close-loop system

In the above block diagram, $y_1 = [\dot{v}_x \ \dot{v}_y \ \dot{r}]^T$ is the vector of the output signals and $y_2 = [v_x \ v_y]^T$ are the measured signals as the input to DCIM which stands for the driver command interpreter module and its function is to map the driver's command signals to the target C.G. forces. The details of DCIM are explained in the next section.

DRIVER COMMAND INTERPRETER

In some references [12], [13], [14] this module has been defined as upper-controller which its function is to generate the desired signals so as to keep the vehicle in stable regions. However, this concept may result in over-restricting the driver in emergency cases. In such a case, the controller may keep the vehicle in stable region at cost of over-riding driver's control capability on the vehicle. Furthermore, in order to have the vehicle stable within the limits of both vehicle and road, the reference signals should be such that the vehicle can be reactive to commands of the driver. To address these

issues, the objective of DCIM developed in this paper is defined to just generate target signals based on commands provided by driver in normal driving conditions.

A driver typically manipulates the vehicle through the steering wheel and gas/brake pedal in order to achieve intended directional motion. Since the objective of the controller is to provide the driver with the same driving experience as that on a dry road conditions with a normal tire characteristics, it is assumed that, in DCIM, the road surface coefficient, μ , is equal to one and the tire characteristics are not subject to aging and wearing. Efficiency and accuracy are two conflict objectives which have to be considered in developing of DCIM. The module should be enough computationally efficient for real-time implementation while enough accurate to avoid over/under estimating driver's intent. With consideration of physical limitations, a nonlinear vehicle bicycle model is utilized to map the driver manipulation signals to controller reference signals (defined as desired C.G. forces) while maintaining reasonable limits to them. Then, when needed, the controller generates the proper control actions based on these data.

The following equations represent the dynamics of a vehicle bicycle model.

$$F_x^* = f_{xf} \cos(\delta_f) - f_{yf} \sin(\delta_f) + f_{xr} + (rv_y + H_{RC} \dot{\phi}) \quad (11)$$

$$F_y^* = f_{xf} \sin(\delta_f) + f_{yf} \cos(\delta_f) + f_{yr} - (rv_x - H_{RC} \dot{\phi}) \quad (12)$$

$$M_z^* = f_{xf} \sin(\delta_f) L_f + f_{yf} \cos(\delta_f) L_f - f_{yr} L_r + I_{xz} \ddot{\phi} \quad (13)$$

The roll angle can be estimated by a single degree of freedom roll dynamic model:

$$\ddot{\phi} = \frac{1}{I_x} [-mH_{RC}(\dot{v} + ru) + mgH_{RC}\phi - K_\phi\phi - C_\phi\dot{\phi} + I_{xz}\dot{r}] \quad (14)$$

The dynamics of wheels are modeled as:

$$\dot{\omega}_i = \frac{1}{I_w} (Q_i - f_{xi} R_t) \quad (15)$$

where $i: f, r$. The tire forces f_{xi} , and f_{yi} are calculated using a nonlinear combined slip tire model.

$$f_{xi} = f_x(\kappa_i, F_{zi}) \cdot \phi_x(\kappa_i, \alpha_i) \quad (16)$$

$$f_{yi} = f_y(\alpha_i, F_{zi}) \cdot \phi_y(\kappa_i, \alpha_i) \quad (17)$$

where

$$f_x(\kappa_i, F_{zi}) = c_{1xi} F_{zi} \sin[c_{2xi} \tanh(c_{3xi} \cdot \kappa_i)] \quad (18)$$

$$f_Y(\alpha_i, F_{zi}) = c_{1yi} F_{zi} \sin[c_{2yi} \tanh(c_{3yi} \cdot \kappa_i)] \quad (19)$$

and

$$\phi_x(\alpha_i, \kappa_i) = [1 - \lambda_{xi} \operatorname{sech}(\gamma_{xi} \cdot \kappa_i) \tanh(\beta_{xi} \cdot \alpha_i)^2] \quad (20)$$

$$\phi_y(\alpha_i, \kappa_i) = [1 - \lambda_{yi} \operatorname{sech}(\gamma_{yi} \cdot \kappa_i) \tanh(\beta_{yi} \cdot \alpha_i)^2] \quad (21)$$

and

$$\kappa_i = \frac{v - r\omega_i}{\max(v, r\omega_i)} \quad (22)$$

$$\alpha_i = \delta_i - \tan^{-1}\left(\frac{v + L_i r}{u}\right) - C_{roll} \phi \quad (23)$$

The weight of the vehicle is assumed to be equally distributed on the front and rear wheels.

$$F_{zi} = \frac{mg}{2} \quad (24)$$

Based upon the tire/road conditions, it is required to define an upper-bound on desired forces calculated in (11), (12), (13) in order to avoid generating excessive side and longitudinal slips. In steady state and stable conditions without side-slip, the upper-bound are defined as follows:

$$F_x^* \leq \mu \sum_{i=1}^2 \left(\frac{Q_i}{R_i}\right) \quad (25)$$

$$F_y^* \leq \mu mg \quad (26)$$

$$M_z^* \leq I_z \frac{d}{dt} \left(\frac{a_y}{v_x}\right) \quad (27)$$

For cases in which any of target signals goes greater than upper value, the upper bound will be considered as the target value.

IMPLEMENTATION ISSUES AND SOLUTIONS

Before compiling the controller codes onto the on-board vehicle microprocessor, some modifications and tunings are performed to solve some real-time implementation issues.

The first issue was associated with differences in the sample times of the DCIM and the sensors. The differences between these sample times make the closed-loop system prone to instability, due to errors in the DCIM outputs. It was noted that different sample times cause the inputs to the DCIM not to be updated properly. This issue was resolved by internally predicting the data for the missing sample-times.

As shown in figure 2, sensory data are fed to the DCIM at time t , while the calculated desired forces are produced at time $t + n \cdot \Delta t$, where Δt is the sampling time of the DCIM and n is the number of missing sample times. Thus, the DCIM requires updating its parameters in this time span by running the built-in vehicle dynamics model. In this work, the sample time considered for the developed DCIM is smaller than the sample time for sensors and hardware communications.

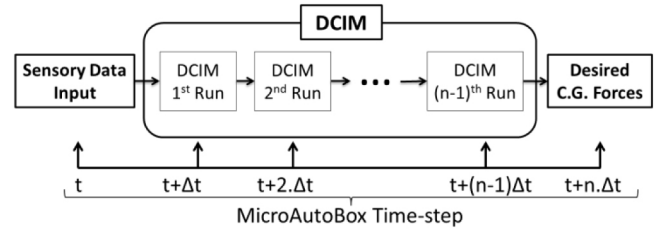


Figure 2. DCIM internal prediction

The second issue was related to existing noises in the outputs of the steering-column sensor and the wheels' optical sensors, which made the signals calculated by the DCIM noisy. In addition, low-frequency noises were observed in the vehicle's IMU signals, causing large discrepancies/errors in the C.G. forces of the proposed controller. These noises were removed by applying Chebyshev filters to the signals of both the DCIM and the IMU. The main reasons for choosing this filter for this application are its fast response time, and its more reliable real-time performance compared to other low-pass filters. As shown in figure 3, this Chebyshev lowpass filter is free of ripple in the passband region, while there might be ripples in the stopband region. The gain of this filter is:

$$G_n = \frac{\varepsilon}{\sqrt{1 + \varepsilon^2}} \quad (28)$$

where the ripple factor (ε) is equal to:

$$\varepsilon = \frac{1}{\sqrt{10^{0.1\gamma_{filter}-1}}} \quad (29)$$

The cutoff frequency (F_h) of the filter is determined by the -3 dB point of the filter magnitude response relative to the peak passband value, and the stopband edge frequency (F_c) is related to F_h by:

$$F_c = F_h \cdot \cosh\left(\frac{1}{n} \cosh^{-1} \frac{1}{\varepsilon}\right) \quad (30)$$

This filter has steeper transition-region roll-off, but more nonlinear-phase response characteristics.