

Optimal Tire Force Allocation by Means of Smart Tire Technology

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ABSTRACT

The effectiveness of active vehicle safety systems soars with the advances in on-board electronics that allows increasingly complex algorithms to be implemented. Numerous studies expose statistical results that underline the rate of reduction in the involvement of the vehicles equipped with such systems in road accidents. These facts clearly indicate how much the current systems have advanced. Nevertheless there are several areas of improvement for these systems, among which utilizing more information about tire-road states (e.g. tire forces, tire slip and slip-angle, surface friction) ranks very high due to the key role tires play in providing directional stability and control. This study introduces the use of an arriving technology, namely the smart tire technology, to estimate and utilize the aforementioned tire-road states along with an optimal tire force allocation scheme for improved vehicle stability. Based on smart tire data collected using the prototype developed at the Center for Tire Research, an observer scheme is proposed which estimates the lateral and longitudinal tire forces. Lyapunov's direct method is utilized for developing the upper level controller while Quadratic Programming (QP) is used to solve the optimality problem for the tire force allocation which ensures that the control system does not push the tires into the saturation region where the vehicle response dramatically deviates from the expected. The resulting tire forces are then applied through differential braking and torque distribution schemes that are assumed to be available on the vehicle. The proposed control algorithm is implemented in the MATLAB/Simulink® environment and evaluated using a D-class sedan vehicle model downloaded from CarSim®. Finally the results of the execution of a double lane change maneuver are presented in addition to a discussion about the advantages the proposed method has to offer.

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INTRODUCTION

Drivers control the vehicle dynamic behavior through steering and braking/acceleration commands resulting in the forces generated at the tire-road contact. Therefore, it is fair to claim that tires have a key role in developing vehicle safety systems. As generally known, these forces highly depend on the road conditions and change with respect to the surface friction. The common characteristics of tire forces on any surface include a linear region where the forces vary linearly with respect to the relative slip values; and a nonlinear region where the forces saturate and may even start decreasing. The experience of most of the daily drivers on the roads is limited within this linear region where the dynamic behavior of the vehicle remains proportional to the driver's inputs. Therefore

an unexpected change in tire characteristics (due to a change in surface friction, large driver inputs, etc.) may easily cause the driver to panic and/or to lose his/her ability to maintain a stable vehicle. These types of instabilities underline the importance of monitoring and utilization of the dynamic variations of the tires and tire-road contact for improved vehicle controls and pose it as a novel engineering problem.

The active safety systems available today seek to prevent such unintended vehicle behavior by assisting drivers in maintaining control of their vehicles. Integrating various control algorithms is a popular solution to improve vehicle performance and to generate direct control on multiple axes of tire forces at the same time. Significant amount of research has been reported on the integration of various control

algorithms [1]. Recently several studies have been focused on the problem associated with distribution of tire forces, as proper utilization of the tire forces is vital for the effectiveness of the control algorithm as mentioned above. A relatively early investigation in the subject is done by Mokhiamar and Abe [2] where the authors used a sliding mode approach to derive the target vehicle characteristics and proposed a cost function based on the tire friction circle phenomena to optimally distribute the tire forces. A similar study is carried out by Wang and Longoria [3] which details a different approach for the force allocation problem based on least squares method. Another study by Plumlee et.al. [4], focuses more on the details of the control allocation problem. The authors propose an optimal control scheme for target states and investigate the computational efficiency of two different control allocation approaches based on quadratic programming to achieve these targets. In [5, 6] and [7] Yu et.al. introduce the dual-loop notion which problem is handled as the servo loop or lower control. The authors utilize frequency response approach for robustness of the upper level control and use an inverse linearized vehicle model in the lower level control to be able to directly compute the actuator commands.

As these results suggest, currently available systems have advanced in many aspects and have indisputable improvements over vehicle stability; nevertheless, the lack of knowledge about the tire-road interactions highly limits their effectiveness. Being in a critical position, tires basically dictate the motion of the vehicle chassis which underlines the significance of these parameters in any control system design. Regarding these facts, recent studies in the field introduced the smart tire technology as a solution for dynamic tire monitoring. The smart tire technology suggests instrumenting the tire for obtaining information on the momentary variations on tire conditions and tire-road interactions. This study examines the potential performance improvements offered by utilizing dynamic tire slip-angle information provided by a robust estimating scheme in an adaptive stability control algorithm. The proposed tire slip-angle estimation scheme makes use of a smart tire prototype which can provide tire's inertial acceleration information and a model based observer which utilizes chassis acceleration and yaw-rate information. The resulting system ensures robust tire slip-angle estimation performance even under extreme maneuvers that run the tire into the saturation region. The proposed control algorithm utilizes the tire slip-angles as the system states and computes control laws to maintain vehicle stability. The algorithm integrates Active Front Steering (AFS) and Direct Yaw Control (DYC) schemes to implement the resulting control laws. The steering command is implemented as an auxiliary input to the driver's steering. As for the yaw control, a lower level control algorithm is developed where the optimal brake forces are calculated that will generate the required yaw moment on the vehicle chassis. The optimization is based on a cost function that consist of the error in the required and available tire forces

and in control commands to avoid tire saturation and keep vehicle stability at the same time.

The rest of this paper details the derivation of these estimation and control systems. The introduction is followed by the explanation of the development and implementation of the tire slip-angle estimation scheme. In what follows, the details of the derivation of the control algorithm are explained. Finally the results of the simulation studies to evaluate the control algorithms are provided. The paper is concluded by discussing the results and the benefits of the proposed systems.

TIRE SLIP-ANGLE ESTIMATION

This section details the two steps of the proposed tire slip-angle estimation scheme. First the instrumented tire based method is introduced which is followed by the observer based system where the longitudinal and lateral tire forces are estimated using a robust sliding mode observer (SMO) scheme and a Luenberger observer is implemented for tire slip-angle estimation using a four wheel vehicle model.

Instrumented Tire Based Estimation

This section presents an implementation strategy for the real-time estimation of the tire-slip angle using accelerometer signals from an intelligent tire. The instrumented tire system was developed by placing accelerometers on the inner liner of a tire ([Figure 1 \(a\)](#)). [Figure 1 \(b\)](#) shows the final assembly of the instrumented tire with a high speed slip ring attached to the wheel. Extensive outdoor tests of the tire were conducted using the in-house mobile tire test rig shown in [Figure 1 \(c\)](#) and [Figure 1 \(d\)](#).

For developing a slip angle estimation algorithm, we especially were interested in determining synthetic parameters that were sensitive to slipangle. Through extensive parametric studies, the key parameter identified was the magnitude of the lateral acceleration signal. The magnitude of the lateral acceleration signal was characterized by estimating the signal power (absolute amplitude of the signal) on a per revolution basis ([Figure 2 \(a\)](#)). A strong dependence of the identified parameter was also seen on the tire loading condition. Hence, one would need to take into account the effect of tire load while estimating the signal power. In the absence of the vertical load information during the online estimation procedure, it became necessary to correlate the accelerometer signal to the instantaneous vertical load. To achieve this objective, the total radial acceleration signal power was estimated on a per revolution basis ([Figure 2\(b\)](#)). From ([Figure 2\(b\)](#)), we can see that the signal power estimates were seen to correlate to the applied vertical load with distinct boundaries demarcating the change in the instantaneous load.



Figure 1. (a) Accelerometer placed on the tire inner-liner (b) Instrumented tire assembly (c) Mobile tire test rig (d) In-house tire testing trailer at the ITL facilities

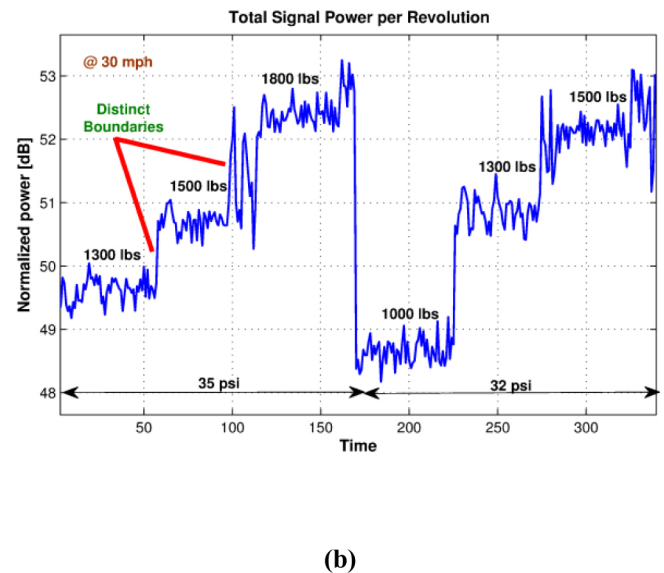
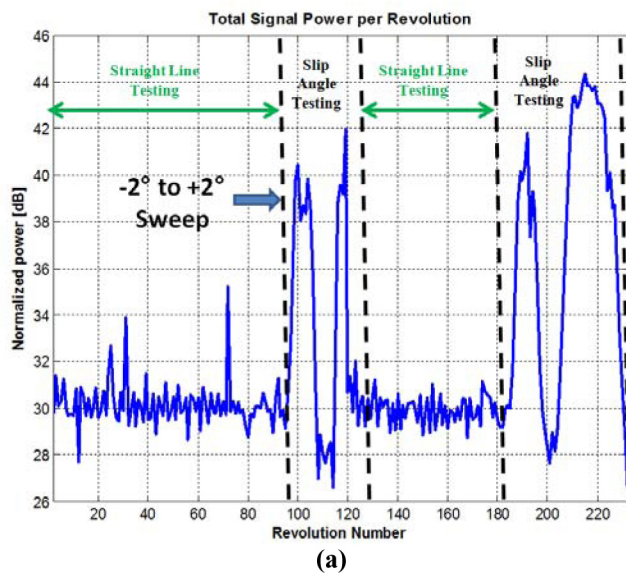


Figure 2. (a) Instantaneous lateral acceleration signal (b) Variation of the radial acceleration signal w.r.t. tire load

Finally, a line-fit algorithm was employed to estimate the slip angles. The tire-slip angles were estimated accurately up to a slip angle of 4° (Figure 3). However, in the estimation of higher slip angles the nonlinear characteristic of the tire dominates the results. To ensure robust performance even during the vehicle maneuvers which show highly nonlinear tire characteristics, a sensor fusion approach, combining the intelligent tire slip-angle estimate with a model based estimate is proposed (Figure 4). The model based estimation methodology uses a tire force estimator in conjunction with a Luenberger observer to make dynamics estimates of the tire slip-angle.

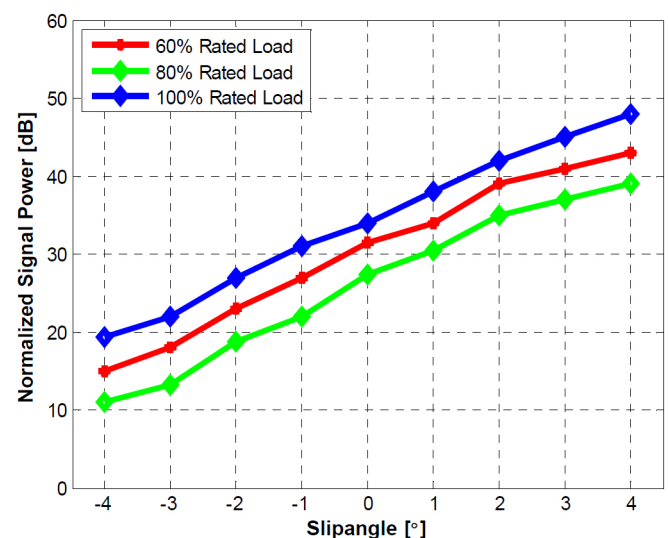


Figure 3. Results of the line-fitting algorithm used in instrumented tire based estimation

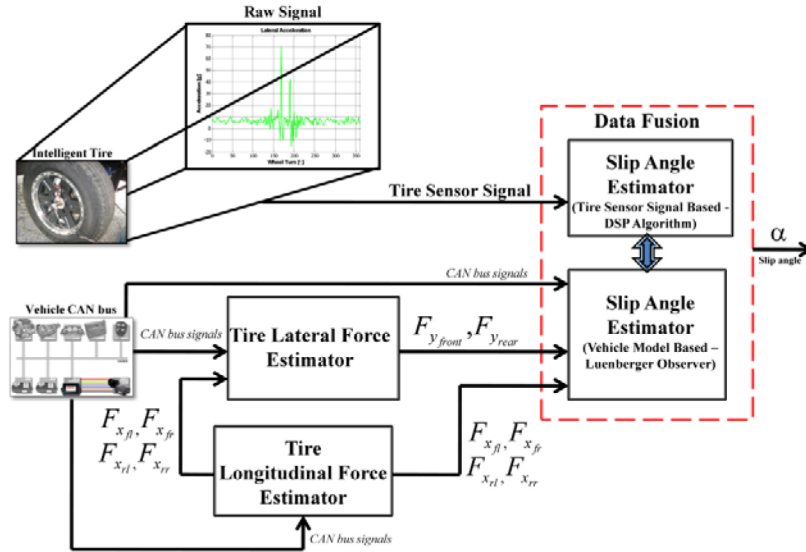


Figure 4. Functional diagram of the tire slip angle estimation process.

Details regarding the methodology adopted to estimate the tire slip angle using an observer based approach are presented in the following section.

Observer Based Estimation

The derivation for longitudinal and lateral force estimators are undertaken in two separate subsections due to their distinct dynamics. The longitudinal force estimation is based on individual wheel dynamics whereas lateral forces are derived using a four wheel vehicle model.

Longitudinal force estimation

Initial derivation of the tire longitudinal forces is based on a simplified model for each individual wheel. The dynamic equation for the angular motion of an individual wheel can be written as:

$$J_w \dot{\omega}_i = T_{w_i} - T_{b_i} - F_{x_i} R_{w_i} - F_{rr_i} R_{w_i} \quad (1)$$

where the subscript $i = fl, fr, rl, rr$ is used to separately represent the four wheels of the vehicle. T_{w_i} , T_{b_i} , R_{w_i} , F_{rr_i} and F_{x_i} represent the drive and brake torque delivered to each specific wheel, the effective radius of the tire, the rolling resistance force and the longitudinal tire force of that specific wheel respectively. Rearranging equation (1) yields an expression for the longitudinal force as:

$$F_{x_i} = \frac{T_{w_i} - T_{b_i} - J_w \dot{\omega}_i}{R_{w_i}} - F_{rr_i} \quad (2)$$

where the wheel drive torque T_{w_i} can be estimated using the engine torque, the engine angular velocity, and the wheel angular velocity [8]. It is assumed that the brake pressure of each wheel is an available signal. Therefore, the brake torque

T_{b_i} can be computed by the brake gain (K_{bf} , K_{br}). The wheel rolling resistance force, F_{rr_i} , is given by the expression:

$$F_{rr_i} = 0.005 + 3.24 \times 0.01 x (R_{w_i} x \omega_i)^2 \quad (3)$$

Even though equation (2) presents a relatively simple (open-loop) method to estimate the longitudinal tire force, it is not advisable to use this approach, since in real-world conditions, finding the time derivative of angular wheel speed signals ($\dot{\omega}_i$) can pose some challenges. To avoid the need of taking derivatives, the use of a SMO scheme is proposed. A random walk model is utilized for longitudinal force dynamics [9] (i.e. $\dot{F}_{x_i} = 0$). As a result, the state estimates ($\hat{w}, \hat{F}_{x_i}$) evolve according to the wheel dynamics (equation (1)) and the random walk force dynamics. Using the sliding mode structure, the sign of the measurement estimation error can be introduced to the system and the final update equations can be written as:

$$J_w \dot{\hat{\omega}}_i = (T_{w_i} - T_{b_i}) - \hat{F}_{x_i} R_{w_i} - F_{rr_i} R_{w_i} + k_1 \text{sgn}(\omega_i - \hat{\omega}_i) \quad (4)$$

$$\dot{\hat{F}}_{x_i} = k_2 \text{sgn}(\omega_i - \hat{\omega}_i) \quad (5)$$

where k_1 and k_2 are the observer gains and $\text{sgn}(\cdot)$ denotes signum function. The results (Figure 5) show that the estimated longitudinal force using the proposed observer formulated using equations (4) and (5) ensures stable estimation of the tire longitudinal force.

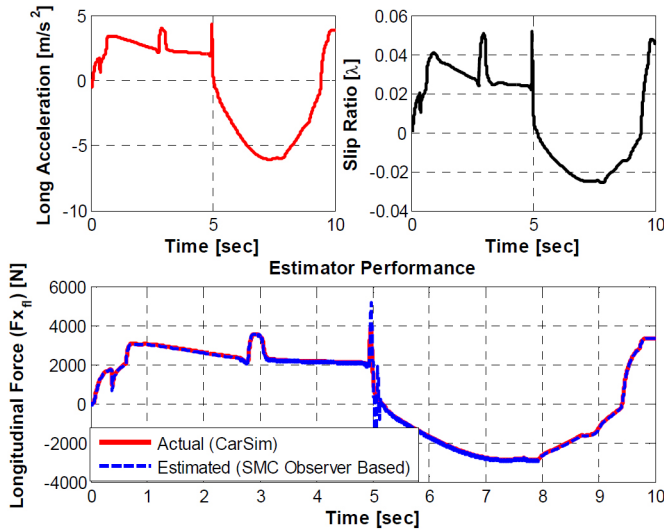


Figure 5. Results of the observer based longitudinal tire force estimation algorithm

In the case of a normal driving situation, the estimators designed at the previous time instant show good performance. However, during extreme maneuvering conditions, where the slip-ratio is large, the performance of the estimator is not satisfactory, since the longitudinal tire-force estimator based on wheel dynamics model does not take into consideration the effects of deformation slip or wheel slip. To overcome this drawback (unsatisfactory performance under high-slip conditions) of a wheel dynamics based observer, a tire model-based closed-loop feedback observer is proposed. The estimator concept used here relies on a physically derived tire model called the Dugoff tire model. In its simplest formulation, the model describes the relationship between the tire force and the slip as a function of two parameters, the tire stiffness ($C_{(x,y)}$) and the tire/road friction coefficient (μ). The tire stiffness describes the inclination of the force-slip relation at small slips whereas the friction coefficient describes its curvature and peak value. The Dugoff-tire model can be expressed as follows:

$$F_x = C_x \frac{s}{1+s} f(\lambda) \quad (6)$$

$$F_y = C_y \frac{\tan(\alpha)}{1+s} f(\lambda) \quad (7)$$

where λ is related to the tire/road friction coefficient. λ and $f(\lambda)$ are defined as follows respectively:

$$\lambda = \frac{\mu F_z (1+s)}{2\sqrt{(C_x s)^2 + (C_y \tan(\alpha))^2}} \quad (8)$$

$$f(\lambda) = \begin{cases} (2-\lambda) \cdot \lambda, & \lambda < 1 \\ 1, & \lambda \geq 1 \end{cases} \quad (9)$$

Shown in Figure 8 (a) is a comparison of the longitudinal forces calculated by the Dugoff and MF tire model. Comparing results from Figure 6 (a), we see that, there is no peak point in the Dugoff model, and the peak value is much smaller than the MF model. Also, the difference in the two models is larger when the slip-ratio is high (i.e. we see a larger difference in the unstable/saturation region).

Previous publications [10] have shown that the above-stated discrepancies between Dugoff-tire and MF-tire models can be reduced if different tire/road friction coefficients are taken for different magnitudes of slip-ratio. Force calculations based on the modified Dugoff tire model are shown in Figure 6 (b). The results are seen to be coincident to the MF tire model. Hence, the estimator concept proposed here is based on the modified Dugoff tire model.

As mentioned previously, the Dugoff model describes the relationship between the tire force and the slip as a function of two parameters, the tire stiffness and the tire to road friction coefficient. In the small-slip range, the longitudinal force increases proportional to the slip and the gradient of the force-slip curve is defined as the tire longitudinal stiffness. Thus, the longitudinal force model in the small-slip range can be expressed as follows:

$$F_x = C_x \lambda, \text{ for } |\lambda| < 3\% \quad (10)$$

Satisfactory performance of the wheel dynamics based observer in the small slip ($|\lambda| < 3\%$) region provides us with an opportunity to adaptively estimate the longitudinal stiffness of the tire using an on-line parameter estimation algorithm. Equation (18) can be rewritten into a standard parameter identification form as follows:

$$y(t) = \varphi^T(t) \theta(t) \quad (11)$$

where $y(t) = F_x$ is the system output (from the wheel dynamics based observer), $\theta(t) = C_x$, is the unknown parameter and $\varphi^T(t) = \lambda$ is the measured slip ratio. The unknown parameter $\theta(t)$ can be identified in real-time using parameter identification approach. The recursive least squares algorithm [11] provides a method to iteratively update the unknown parameter at each sampling time to minimize the sum of the squares of the modelling error using the past data contained within the regression vector, $\varphi(t)$. The performance of the RLS algorithm is evaluated with simulations where the road surface is designed to have sudden friction coefficient changes, and the vehicle manoeuvre is straight driving with intermittent gas pedal presses.

From Figure 7, we see that, the estimator shows delayed estimation at the first change due to lack of excitation at that time. Once excitation occurs at 2.2 seconds, the estimator updates the longitudinal stiffness. In Figure 7 (b), at the time of the second surface change (4.8 seconds), the excitation duration is coincident with the change so that the estimated friction coefficient tracks the actual value immediately.