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Vehicle sideslip estimation: A kinematic based approach☆

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ABSTRACT

This paper deals with vehicle sideslip angle estimation. The paper introduces an industrially amenable kinematic-based approach that does not need tire–road friction parameters or other dynamical properties of the vehicle. The convergence of the estimate is improved by the introduction of a heuristic based on readily available inertial measurements. The method is tested on a vast collection of tests performed in different conditions, showing a satisfactory behavior despite not using any information on the road friction. The extensive experimental validation confirms that the estimate is robust to a wide range of driving scenarios.

1. Introduction

Over the last few decades, industrial and academic research has dedicated great effort towards safer and better performing four-wheeled vehicles. Sensors and actuators evolution (Leen & Heffernan, 2002; Van Zanten, 2002) has made possible the use of advanced control techniques acting on vehicle dynamics with the aim of generating suitable yaw moment to avoid dangerous conditions or increase performances. Nowadays electronic stability control (ESC) is a standard technology in almost all commercial passenger cars (Laine & Andreasson, 2007; Piyabongkarn, Lew, Rajamani, Grogg, & Yuan, 2007), while researchers continue to explore the possibility of using rear axle steering to improve the vehicle stability (Marino, Scalzi, & Cinili, 2007; Selmanaj, Corno, Sename, & Savaresi, 2013). From a control standpoint, besides the problem of defining the control laws, the knowledge/measurement of vehicle states presents a challenge.

From the vehicle stability standpoint, the most important states are sideslip angle, *i.e.* the angle between the vehicle longitudinal axis and the direction of the vehicle velocity, and the sideslip rate. These are used to determine the control action, re-schedule the parameters of the control architecture or re-establish the vehicle stability. To these ends the fast and road-independent estimation of the two quantities is crucial, He, Crolla, Levesley, and Manning (2006) and Koibuchi, Yamamoto, Fukada, and Inagaki (1996).

The sideslip angle and its rate can be measured via optical sensors or GPS with sufficient accuracy in all road conditions; however these solutions are prohibitively expensive for commercial cars (optical sensors) or lack reliability (GPS). Methods for integrating inertial measurements with low-cost GPS measurements (Bevly, Gerdes, and Wilson, 2002; Bevly, Ryu, and Gerdes, 2006; Li, Chan, and Wang, 2016; Ryu, Rossetter, and Gerdes, 2002; Yoon and Peng, 2014a, b, for example) or tire force sensors (Madhusudhanan, Corno, and Holweg, 2016; Nam, Fujimoto, and Hori, 2012, for example) have been proposed. However, GPS is not present in all commercial vehicles and tire force sensors introduce excessive costs and complexity to the vehicle design (Corno, Gerard, Verhaegen, & Holweg, 2012; Kunnappillil Madhusudhanan, Corno, & Holweg, 2015). Therefore, online estimation techniques using low-cost inertial sensors have been widely studied in the automotive research. The proposed method exploits low cost off-the-shelf measurements, *i.e.* vehicle accelerations along the three axis, vehicle angular rates, wheel angular rates and wheel steering angle.

In the realm of methods using standard measurements, there exist two main families of approaches: black-box or white-box estimation. Black-box approaches derive methods that directly estimate the sideslip angle from the measurements. Assuming the sideslip angle as a nonlinear function of the yaw rate and the lateral acceleration, a neural network can model the vehicle behavior and can be used to estimate the sideslip angle, Sasaki and Nishimaki (2000). The main drawback of the method is that it does not consider the relation with the vehicle speed. A similar method is used in Milanese, Regruto, and Fortina (2007). The authors propose a nonlinear estimator, designed based on the direct virtual sensor approach. A neural network exploits the lateral acceleration, steering angle, yaw rate and longitudinal velocity

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measurements and forms the core of the estimator. Despite showing promising performance, both papers do not consider the effect of road friction in the analysis. Varying road conditions could affect the estimation accuracy. These are data driven approaches; if the training set has not considered a particular type of ground, there is no way of guaranteeing how the estimator will behave when driving on such roads.

For these reason, most solutions include model-based estimation techniques. An important aspect classifying these methods is the vehicle model type; two main categories can be identified: dynamic model-based and kinematic model-based methods.

Dynamic models provide a good description of the vehicle lateral dynamics, but require a good knowledge of the vehicle parameters, specially tire–road interaction conditions. As a matter of fact, the tire friction model and its online estimation plays a key role in many studies. A sliding mode observer, with a simplified tire model, is proposed in Stephant, Charara, and Meizel (2007), and is shown to have good results with lateral acceleration not exceeding 0.6 g (*i.e.*, linear region). In Baffet, Charara, and Lechner (2009), the authors present a two-step method: the first step includes a sliding mode observer that provides the tire–road forces while in the second step an Extended Kalman Filter (EKF) estimates the sideslip angle and the cornering stiffness. Wenzel, Burnham, Blundell, and Williams (2006) presents a dual EKF method. Two filters run in parallel, one dedicated to the estimation of the vehicle state while the others estimates. Alternative solutions relying on the EKF are presented in Coyte et al. (2014), where a decision tree classifies the uncertainties and disturbances to assist an EKF, and in Dakhlallah, Glaser, Mammar, and Sebsadji (2008), where the vehicle state and the tire–road forces are reconstructed. A critical point of dynamic model-based methods is the difficulty of estimating the tire friction. This task requires exciting running conditions, which are not always verified. Indeed, the aforementioned methods are validated on exciting maneuvers and lack extensive analysis during low excitation tests. Furthermore, dynamic models lose their reliability on high acceleration conditions where the vehicle dynamics becomes nonlinear, mainly due to tires behavior. Experimental results of aforementioned solutions present limited lateral accelerations (0.6 g). Other disadvantages regarding these methods concern the vehicle mass and yaw inertia sensitivity; both parameters can experience large variations.

An alternative approach are kinematic model-based methods, which rely on a simple vehicle model that correlates the vehicle longitudinal and lateral velocities with longitudinal and lateral accelerations and the yaw rate. These methods do not depend on vehicle or tire friction parameters. A well known nonlinear vehicle state observer was introduced in Farrelly and Wellstead (1996) and proved to be asymptotically stable for all cornering conditions (non-zero yaw rate). In Panzani et al. (2010), the authors strengthen the aforementioned method proposing an online offset estimation via a recursive identification approach. An EKF designed on the kinematic model is presented in Kim and Ryu (2011); the effectiveness of the method is shown on short maneuvers (10 s). Based on the same model, in Wei, Wenying, Haitao, and Konghui (2012) the authors propose a sliding mode observer; the observer is tested and analyzed on a simulation environment and a double lane change maneuver. According to the best of our knowledge and literature research, these are the only studies relying on a pure kinematic model and are all analyzed on simulation data or short duration experiments. All results evidence that kinematic model-based methods are reliable for transient maneuvers, but they suffer from estimation errors on nearly steady-state conditions.

One option for overcoming these limits is to design observers that join the advantages of the kinematic and dynamic model. The method proposed in Cheli, Sabbioni, Pesce, and Melzi (2007) relies on the kinematic formulation during transient maneuvers and on a state observer, designed on the single track model, on nearly steady-state maneuvers. During transient maneuvers the kinematic estimate is used to update the friction parameters of the single track model. Experimental results prove the validity of the method. In Fukada (1999), a feedback algorithm is fed with the side force estimated from the lateral acceleration and the side force given by a tire model with an online estimate of the road friction coefficient. Other methods mixing the two approaches are shown in Oh and Choi (2012) and Piyabongkarn, Rajamani, Grogg, and Lew (2009). Both studies combine a kinematic model and a bicycle model with online friction adaption through a weighted mean; experimental results for the standard double lane change maneuver are shown. In Grip et al. (2008), the authors present a method based on a nonlinear observer. The method joins a kinematic model with a correction term computed on a friction model which is estimated online. In Grip, Imsland, Johansen, Kalkkuhl, and Suissa (2009); Imsland et al. (2007) an online road banking estimation is added and the results are compared with an EKF. The proposed approach is tested on different experimental tests. However, exciting running conditions (*i.e.*, varied driving path) are essential for the stability of the method and solutions for particular driving conditions have been found.

Although different architectures can be used to combine the kinematic and the dynamic model, Han and Huh (2011), and some studies show good results on standard maneuvers, the excitation of the driving conditions remains a major limitation. Especially on strong curves following long straight drivings (*i.e.*, when the friction estimation cannot be updated) and when the friction experiences step variations during curves, methods relying on the friction estimation are more prone to sideslip estimation errors. The present work aims to give a reliable solution to the sideslip angle estimation problem without the need of estimating the friction parameters and is based on the kinematic approach. First, the observer proposed in Farrelly and Wellstead (1996) is modified to overcome the unobservability for zero yaw rate conditions without using the dynamical model (or road parameters); the method relies on a heuristic that drives the sideslip angle estimation to zero when the vehicle is moving straight. The heuristic is computed as a static function of the inertial measurements. Therefore, a method for the online offset estimation and one for the vehicle longitudinal speed estimation are proposed. The validity and reliability of the method is shown on several realistic driving tests representing hours worth of driving. These tests include highly dynamic and nearly steady state maneuvers. To the best of the authors knowledge this paper represents the most thorough experimental validation of a sideslip angle estimation available in the open scientific literature. Results on different road conditions demonstrate the robustness of the method to varying road conditions. The method and the equations are described in continuous time. However, to obtain the experimental results, the method has been implemented on an off-the-shelf electronic control unit running at 100 Hz.

The paper is organized as follows. In Section 2 the kinematic observer and the longitudinal vehicle speed estimation are described. Section 3 describes the structure of the estimation method including the kinematic observer, the offset estimation, the roll angle estimation and the undesired effects compensation. In Section 4, the offset estimation algorithm is presented. In Sections 5 and 6, experimental results are shown and sensitivity to vehicle mass and road surface is analyzed. The paper ends with some concluding remarks. Part of the present work is protected by the patent (Selmanaj et al., 2016).

2. Kinematic model-based observer

The vehicle state observer is based on the kinematic model shown in (1), and quantities refer to the schematic of Fig. 1. The model relates the vehicle accelerations (A_x and A_y) to the vehicle velocities derivatives ($\dot{V}_x$ and $\dot{V}_y$) and the yaw rate (ω_z). For straight movement, the vehicle accelerations correspond to the vehicle velocities derivatives. As the vehicle turns, the longitudinal acceleration is influenced by the lateral velocity (V_y) and the yaw rate while the lateral acceleration is influenced by the longitudinal velocity (V_x) and the yaw rate.

$$\begin{cases} A_x(t) = \dot{V}_x(t) - \omega_z(t) V_y(t) \\ A_y(t) = \dot{V}_y(t) + \omega_z(t) V_x(t). \end{cases} \quad (1)$$