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New online estimation algorithm of lateral tire-road coefficients based on Inertial Navigation System

Laëtitia Li¹, Brigitte d’Andréa-Novel²,³ and Sylvain Thorel⁴

Abstract—For the sake of simplicity, control laws for autonomous vehicle mainly use linear tire models, but this modeling is only valid for small slip angles. Hence, to keep this hypothesis valid, tire’s behavior has to lie within the limits of handling, i.e. there is a threshold the slip angle cannot surpass. This paper develops a new estimator for the cornering stiffness and maximum lateral friction coefficients. These parameters provide important information on the ground conditions and are beneficial for improving the stability of the vehicle. The algorithm is based on estimated lateral tire forces and on a 3 zones adaptive algorithm, including a Dugoff theoretical tire model. It will allow to set up a model not only for the linear part but for the whole range of slip angles, providing the trend of the tire behavior at each time and informing about the future evolution of lateral forces. The advantage of the algorithm is that no measurement of lateral tire forces is needed and few parameters are required such as yaw rate, longitudinal and lateral velocities obtained through an effective Inertial Navigation System, wheel rotational speeds and steering angles. Simulations conducted on realistic dynamical situation validate the algorithm efficiency.

I. INTRODUCTION

Control laws are mainly based on the assumption of linear tire model. Such an assumption is only valid for small slip angle and tire’s behavior becomes highly nonlinear for severe maneuvers, slippery road or at high-speed. To keep this assumption valid, tires slip angle must remain within the limits of linear tire’s behavior which brings us to estimate the slip angle threshold $\beta_{th}$ (see Fig.1). This information can be obtained through the knowledge of maximum lateral friction coefficient. The cornering stiffness $C_g$ is necessary in the context of closed loop in order to use the linear tire model. They are both important parameters of the tire/road interaction which depend mainly on the road conditions and are closely related to the tire efforts. Knowing precisely and in real-time these parameters allows to incorporate them in the control law and thus significantly impact the performance of the controller. As many factors affect the lateral friction coefficient and cornering stiffness, such as road surface conditions, tire types, temperature, tire pressure and so on, the identification of these parameters is still a challenging issue.

Most of the approaches estimating the cornering stiffness use a linear adaptive tire model. For example, [1] and [2] estimate the cornering stiffness based on a gradient search algorithm and [3] uses a Kalman filter. Concerning tire-road friction coefficient, many researches have been done. Some of them try to estimate the parameters that affect the tire-road friction coefficient and try to predict the maximum friction coefficient $\mu_{max}$ by using friction models. These methods require specific sensors (such as tire tread, optical or acoustic sensors) ([4], [5], [6]). In other approaches, researchers measure the effects of friction change on the tire behavior and developed slip-based $\mu_{max}$ estimators [8]. The idea of slip-based estimator is to use the friction vs. slip data curve to identify $\mu_{max}$. The slip-slope of this curve is related to a type of road and allows to establish a friction classifier. Some of the slip based $\mu_{max}$ estimators work during braking [7], while other work during traction ([9],[10]). Slip-based approaches require a minimum of slip for the tire through acceleration, deceleration or steering maneuvers and have problem with calibration. In fact, the slip-slope used to classify the type of roads are sensitive to tire characteristics.

Researchers also developed estimators based on theoretical model forces such as Burckhardt ([11],[12]) and LuGre ([13],[14]) models. These models are complex and the two parameters to be estimated are not clearly expressed. [15] and [16] use a brush tire model in which the two parameters clearly appear but only the friction coefficient is estimated.

All these methods are based on a curve fitting approach and parametric identification to minimize the error between the developed force and the model-based force. To the best of our knowledge, [17] is the only paper estimating both the friction coefficient and the cornering stiffness. It uses a lateral tire model and the estimation is based on a parametric model and an adaptive law.

This paper concentrates on developing and demonstrating a reliable online algorithm for maximum lateral tire-road friction $\mu_{max}$ and cornering stiffness $C_g$ estimation based on Inertial Navigation System measurements such as yaw rate, longitudinal and lateral velocities, as well as rotational speeds and steering angles. We also need a measure of wheel torque which could be given by an additional sensor or by the computed control law itself in a control loop context. The algorithm takes into account the linear and nonlinear part of tire characteristics by using a 3 zones adaptive algorithm. The inputs are the differences between estimated lateral forces and forces calculated with theoretical models: affine, Dugoff and constant. This algorithm includes a Levenberg Marquardt optimization method and a least squares fitting technique.

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The lateral force $F_y$ is mainly influenced by the slip angle $\beta$. This latter is defined as the angle between the direction of the wheel and the wheel speed vector. Fig. 1 shows this function $F_y(\beta)$. The slope at the origin is the so-called cornering stiffness $C_\beta$. As can be seen from Fig. 1, for small values of $\beta$, $F_y$ is proportional to $\beta$. For greater values of $\beta$, $F_y$ saturates. Vehicle dynamics depend on cornering stiffness $C_\beta$ and maximum friction coefficient $\mu_{y_{\text{max}}}$ which are necessary to model the characteristics of tire/ground interaction. The limits of handling are defined from the maximum available lateral force

$$F_{y_{\text{max}}} = \mu_{y_{\text{max}}} F_z$$

where $F_z$ is the vertical tire force. Table I shows some typical value for $\mu_{y_{\text{max}}}$ for different type of roads. The closer $\mu_{y_{\text{max}}}$ is to 1, the bigger $F_{y_{\text{max}}}$.

<table>
<thead>
<tr>
<th>Road conditions</th>
<th>Asphalt dry</th>
<th>Asphalt wet</th>
<th>Snow</th>
<th>Ice</th>
</tr>
</thead>
<tbody>
<tr>
<td>Approximated $\mu$</td>
<td>0.9-1.0</td>
<td>0.5-0.8</td>
<td>0.2-0.3</td>
<td>0.13-0.2</td>
</tr>
</tbody>
</table>

A. Dugoff model

There are many tire models that reflect the highly nonlinear relation between the lateral tire forces and slip angles. These models range from a simple linear proportional model depending only on $C_\beta$ and $\beta$ to a nonlinear model such as the well-known Pacejka model, characterized by numerous empirical parameters [30]. The linear model has been widely used in many applications. This model is suitable for vehicles in normal driving situations where $\beta$ is low. However, as soon as the vehicle is subjected to severe maneuvers, $\beta$ becomes large and $F_y$ has a nonlinear behavior. So, a Dugoff model is chosen to describe the non linearities of tire’s behavior with minimum complexity and qualitative correspondence with experimental behavior. It provides a simple formulation that can describe the forces under pure cornering, pure acceleration braking and combined acceleration (braking)/cornering maneuvers. It assumes a uniform vertical pressure distribution on the tire contact patch.

Longitudinal force is expressed as $F_x = C_\sigma \frac{\sigma_{z_{ij}}}{1 + \sigma_x} f(\lambda)$ (see [33]) and lateral force as:

$$F_y = C_\sigma \tan(\beta) \frac{\sigma_{z_{ij}}}{1 + \sigma_x} f(\lambda)$$

where $f(\lambda)$ is given by:

$$f(\lambda) = \begin{cases} 
(2 - \lambda)\lambda & \text{if } \lambda < 1 \\
1 & \text{if } \lambda \geq 1
\end{cases}$$

$$\lambda = \frac{\mu_{y_{\text{max}}} F_z (1 + \sigma_x)}{2 \sqrt{(C_{\sigma_x} \sigma_x)^2 + (C_{\beta_x} \tan(\beta))^2}}$$

with $\sigma_x$ the longitudinal slip ratio. These two equations depend on 4 important tire’s parameters: the longitudinal stiffness $C_\sigma$, cornering stiffness $C_\beta$, normal force $F_z$ and maximum tire road friction coefficient $\mu_{y_{\text{max}}}$.

Assuming pure slip conditions with negligible longitudinal slip, the simplified Dugoff model becomes:

$$F_{y_{ij\text{ dug}}} = \begin{cases} 
C_{\beta_{ij}} \tan(\beta_{ij}) & \text{if } \lambda \geq 1 \\
C_{\beta_{ij}} \tan(\beta_{ij}) (2 - \lambda)\lambda & \text{if } \lambda < 1
\end{cases}$$

and $\lambda$ is given by:

$$\lambda = \frac{\mu_{y_{ij\text{max}}} F_{z_{ij}}}{2 C_{\beta_{ij}} \left| \tan(\beta_{ij}) \right|}$$

The subscripts $ij$ here and in the sequel stand for $fl, fr, rl$ and $rr$ which respectively refer to front left, front right, rear left and rear right wheels. The tire force equations clearly show the two unknown parameters to estimate, the cornering stiffness $C_{\beta_{ij}}$ and the friction coefficient $\mu_{y_{ij\text{max}}}$. This model synthesizes all the properties of the tire within these two parameters and this is the advantage compared to the Pacejka model, known as the reference model for the wheel/ground interaction modelling.

However, the accuracy decreases for large slip angles, compared to Pacejka’s model. Indeed, when slip angles become large and enter into the nonlinear part, the forces obtained by the Dugoff model become larger than those computed by the Pacejka model. To briefly illustrate this, let us consider a vehicle moving on the trajectory illustrated in Fig. 6. Under normal driving conditions (lateral acceleration below 0.4g) as shown Fig. 2, on adherent ground like dry asphalt at 14m/s (full red and blue lines), Pacejka and Dugoff
models fit very well. For 19m/s (dotted red and blue lines), as expected, we note that Dugoff’s model slightly overestimates the lateral force when the lateral acceleration is high (0.47g). Despite that, Dugoff model can fit correctly Pacejka model. Additionnaly, as already mentioned in the introduction, the Dugoff model can save computing time and increase robustness compared to variations in road conditions. For example, ([25],[26],[27],[28]) do not use a tire model but neglect rear longitudinal forces (load transfer). By neglecting the coupling between pitch and roll dynamics, the vertical forces are [18]:

\[
F_{z_f} = \frac{m}{2l} g - \frac{h a_x}{2l} - \frac{m a_y l_f}{e_f l} \\
F_{z_r} = \frac{m}{2l} g - \frac{h a_x}{2l} + \frac{m a_y l_f}{e_f l} \\
F_{z_l} = \frac{m}{2l} g + \frac{h a_x}{2l} - \frac{m a_y l_f}{e_f l} \\
F_{z_r} = \frac{m}{2l} g + \frac{h a_x}{2l} + \frac{m a_y l_f}{e_f l}
\]

where \(m\) is the vehicle mass, \(g\) the gravity acceleration, \(h\) the height of the center of gravity, \(a_x\) and \(a_y\) the longitudinal and lateral acceleration at the center of gravity.

C. Longitudinal tire force estimation

Longitudinal tire forces in tire frame \(F_{xp_{ij}}\) can be calculated from the wheel rotation dynamics:

\[
F_{xp_{ij}} = \frac{T_{\omega_{ij}} - I_r \dot{\omega}_{ij}}{r_{ij}}
\]

where \(T_{\omega_{ij}}\) is the wheel torque, \(I_r\) the wheel moment of inertia, \(\dot{\omega}_{ij}\) the angular velocity and \(r_{ij}\) the effective radius of the wheel. Wheel torques are the control variables which are computed if the estimation is integrated into a control loop otherwise torque sensors are needed.

D. Lateral tire force estimation

The problem of estimating lateral tire forces \(F_y\) has been extensively studied in the dynamic vehicle community. Some methods use tire models to estimate axle per axle lateral forces by neglecting rear longitudinal forces ([19],[20]). Other methods are also based on tire models but use a 4 wheels model and estimate the forces via an EKF ([21],[22],[23]) or UKF [24].

In our case, we do not want to use a force model to estimate \(F_y\) because a force model is already used to estimate \(C_{\beta_{ij}}\) and \(\mu y_{ij,\text{max}}\). In addition, not using a complex force model can save computing time and increase robustness compared to variations in road conditions. For example, ([25],[26],[27],[28]) do not use a tire model but neglect rear longitudinal tire forces and estimate lateral tire force per axle thanks to an observer. [29] estimates the lateral tire forces witout using tire model but based on yaw moment calculation \(M_G\) at the center of gravity \(G\) and \(M_{G_{ij}}\) at the center of each wheel \(G_{ij}\), leading to the following equations :

\[
\begin{align*}
M_G &= I_\psi \ddot{\psi} = T_{x_0} + T_{y_0} \\
M_{G_{ij}} &= M_G + m (\vec{a}_G \wedge \vec{G}_{ij}) \cdot \vec{x}_{ij} = T_{x_{ij}} + T_{y_{ij}}
\end{align*}
\]
where $\vec{a}_G$ is the acceleration vector at $G$, $\vec{z}_G$ the vertical axis attached to the vehicle frame and $T_{z*}$ and $T_{z*}$, respectively, include the terms depending on longitudinal and lateral tires forces (see [29]). By adapting [29] to four steering wheels vehicle and lumping (9) as a matrix form gives:

$$\vec{F}_Y = H^{-1} \vec{T}_Y$$

(10)

where

- $T_{yo} = \left( \frac{(T_{y^e1} - T_{y^e1}) + (T_{y^e2} - T_{y^e2})}{2} \right)$
- $F_{ypf} ^{ypf} = F_{ypf} ^{ypf} + F_{ypf} ^{ypf}$
- $T_{z*} = M - T_{z*}$
- $H = \left( \begin{array}{cc}
  l_f \cos(\delta_f) & -l_r \cos(\delta_r)
  \\
  (l_f + l_r \cos(\delta_f)) & (l_f + l_r \cos(\delta_r))
\end{array} \right)$

where $F_{ypf}$ and $F_{ypf}$ stand for the front and rear total lateral force in the tire frame. (10) gives the estimation of front and rear lateral forces per axle and then lateral forces at each wheel are calculated from a vertical force distribution:

$$F_{ypf} = \frac{F_{ypf} - F_{ypf}}{F_{ypf} - F_{ypf}}$$

(11)

In what follows, we call the measured lateral force, the force obtained in simulation with the Pacejka model and the estimated lateral tire forces the ones obtained with (8)-(11). For a lane-change trajectory such as the one depicted in Fig. 6 at 18m/s, Fig. 3 and Fig. 4 respectively show the estimated and measured lateral tire force for the front left wheel. As depicted in Fig. 3, the error is low but reaches 20% when the vehicle takes the corner with a lateral acceleration of 0.4g. Concerning the case shown in Fig. 4 the error reaches 35% during the turn. Thus, it can be noted that the estimation is quite relevant even for high lateral acceleration.

IV. ESTIMATION ALGORITHM OF MAXIMUM LATERAL FRICTION AND CORNERING STIFFNESS

By studying $F_y(\beta)$ curve in Fig. 5, we divide the curve into 3 zones: linear, transitional and nonlinear regimes as depicted in red. For the estimation purpose, we also distinguish 3 others areas of estimation:

- an affine zone belonging to the linear regime where $F_{ypf} ^{ypf} = a_1 \beta_{ij} + b_1$;
- a Dugoff model zone overlapping the transitional regime and a part of the linear and nonlinear regime, where $F_{ypf} ^{ypf} = F_{ypf} ^{ypf}$ (see (2)) ;
- a constant zone belonging to the nonlinear regime where $F_{ypf} ^{ypf} = b_2$

The delimitation of these estimation areas differs from the one usually defined for the tire model regions as depicted in green in Fig. 5. The aim is to find $C_{ij}$ and $\mu_{ij, \text{max}}$ that minimize the error between the lateral force $F_{ypf} ^{ypf}$ provided by the 3 different theoretical models mentioned above and the one estimated with (8)-(11), $F_{ypf} ^{ypf}$. For the affine zone, the linear least squares fitting technique is applied, for the Dugoff model zone, the Levenberg Marquardt (LM) algorithm is used and for the constant zone, the constant $b_2$ is chosen equal to the maximum lateral tire force of the window.

Splitting the estimation into several zones allows us to limit the range where the Dugoff model is applied to prevent from possible errors and wrong convergence due to the LM algorithm. When $\beta$ is very small, lateral forces can be approximated by an affine model. This area is framed by the y-intercept values $b_1$. In the nonlinear region, the constant model is applied. The transition between the different zones is function of the slope $a_1$ and the y-intercepts values $b_1$.

As input for the algorithm, a sliding window is used. It contains a set of $\{F_{ypf} ^{ypf}(k), \beta_{ij}(k), t(k)\}$ data, with $1 \leq k \leq N$, $t$ is the time and $N$ the empirically determined window’s maximum length. Accumulating values over time will avoid to obtain aberrations in the estimation. Trade-off must be made since a large data set causes delays and increases the computational load but it achieves better performance. This window, with variable length, will depend on spatial and temporal factors. With $\epsilon_1$, $\epsilon_2$, $\tau_1$ and $\tau_2$ which are thresholds fixed by the user, the window is constructed as follows:

- a data is added to the window if:
  - the difference between the last slip angle $\beta(k)$ of the window and the current one $\beta(k+1)$ is greater than $\epsilon_1$: $|\beta(k+1) - \beta(k)| \geq \epsilon_1 \rightarrow$ add data
  - there was no data added for a long time:
because the partial derivative is zero. This can be seen Fig. 5. Tires different regimes and zones for estimation.

\[
\beta_t \text{ only needed in the transient and nonlinear area of the tire model. In the linear region, only } \mu_{\beta_{ij}} \text{ is needed. This is not critical because the ratio } \frac{\partial F_{ij}}{\partial \beta_{ij}} = 0 \text{ for which the linear tire model is no longer valid.}
\]

\[
\begin{align*}
\text{if } \lambda \geq 1: & \quad \frac{\partial F_{ij}}{\partial \mu_{\beta_{ij}}} = 0 \\
\text{if } \lambda < 1: & \quad \frac{\partial F_{ij}}{\partial \mu_{\beta_{ij}}} = \frac{\mu_{\beta_{ij}}}{4} \frac{F_{ij}^2}{\tan(\beta_{ij})^2} \\
& \quad \frac{\partial F_{ij}}{\partial \mu_{\max}} = F_{ij} \tan(\beta_{ij}) - \frac{F_{ij}^2}{2C_{ij}}
\end{align*}
\]

Therefore, for small \( \beta \), it is not necessary to use the LM algorithm to estimate the parameters. Since this method does not allow to calculate \( \mu_{\beta_{ij}, \max} \), one can simply calculate \( C_{\beta_{ij}} \) as the slope \( a_1 \) at the origin of \( F_{ij} = a_1 \beta_{ij} + b_1 \) with linear least squares fitting technique. In addition, the Pacejka model does not necessarily pass through the origin unlike Dugoff model, so LM algorithm may have a lower convergence or a larger error than the affine model. This will lead to save computing time and it will allow a good initialization of \( C_{\beta_{ij}} \) before the entrance into the transient regime.

\section*{B. Dugoff model zone}

The optimization is performed using LM method. Let us recall that this iterative algorithm provides a solution to the problem of minimizing a multivariate function. This function is expressed as the sum of squared errors \( J = \sum_{i=1}^{k} (F_i(n) - F_{ij}(n))^2 \), with \( k \) the number of element in the window. The LM algorithm can be seen as a combination of the steepest descent method and Gauss Newton method [34]. As output, the LM algorithm provides the cornering stiffness and maximum lateral friction coefficient.

\section*{C. Constant zone}

In the nonlinear zone, since the Pacejka model decreases whereas Dugoff model remains constant or slightly growing, the data will not follow the model we want to fit which can cause the algorithm to converge to wrong values. In addition, updating \( C_{\beta_{ij}} \) in the nonlinear zone is also risky because several values of \( C_{\beta_{ij}} \) can correspond to a given \( \mu_{\beta_{ij}, \max} \). The use of LM algorithm will not be necessary and a constant model will be sufficient to calculate \( \mu_{\beta_{ij}, \max} \). As previously said, this will lead to save computing time and good initialization when entering in the transient zone. Once the constant zone identified, the constant is chosen as the mean of the lateral forces data included in the window.

\section*{D. Determination of \( \beta_{th} \)}

The purpose of estimating maximum lateral friction coefficient \( \mu_{\beta_{ij}, \max} \) is to calculate the slip angle threshold value \( \beta_{th} \) for which the linear tire model is no longer valid.

The way we choose is to consider the error between the Dugoff model \( F_{ij, \text{dug}} \) for \( \lambda < 1 \), that we call \( F_{ij, \text{dug NL}} \) and the linear model \( F_{ij, \text{lin}} \) \( \mu_{\beta_{ij}} \), \( C_{\beta_{ij}} \). When the tire is in the linear region, the two models approximately coincide and the ratio \( p = \frac{F_{ij, \text{lin}}}{F_{ij, \text{dug NL}}} \) is almost equal to 1. Thus, when \( p \) keep...
becomes bigger than 1, the linear model is no longer true. As
the two thresholds not exactly coincide, we consider that the slip
angle threshold $\beta_{th_{ij}}$ is reached when the ratio is higher than
$p = 1.05$ (experimentally determined). Thus, $\beta_{th}$ is defined
as the angle such as $F_{lin}(\beta_{th}) = 1.05 F_{yj_{max}}(\beta_{th})$. $\beta_{th_{ij}}$ is
obtained as following:

$$p = \frac{C_{\beta_{ij}} \beta_{ij}}{(2-\lambda)\lambda C_{\beta_{ij}} \tan(\beta_{ij})} \approx \frac{1}{(2-\lambda)\lambda}$$  \hspace{1cm} (13)

with $\lambda$ depending on $\beta_{ij}$ (see (3)). Solving this 2nd order
equation in $\beta_{th_{ij}}$ gives:

$$\beta_{th_{ij}} = \frac{4p \mu_{yj_{max}} F_{z_{ij}} C_{\beta_{ij}} \pm \sqrt{\Delta}}{8C_{\beta_{ij}}^2}$$  \hspace{1cm} (14)

where $\Delta = 16p^2 \mu_{yj_{max}} F_{z_{ij}}^2 C_{\beta_{ij}}^2 (p^2 - p)$, $\Delta \geq 0$

To be sure to maintain the tire in the linear part, we choose
the smallest as the threshold :

$$\beta_{th_{ij}} = \frac{4p \mu_{yj_{max}} F_{z_{ij}} C_{\beta_{ij}} - \sqrt{\Delta}}{8C_{\beta_{ij}}^2}$$  \hspace{1cm} (15)

Remark: We could have use the definition of $\mu_{yj_{max}}$ (see
(1)) to calculate the slip angle threshold with $F_{yj_{max}} = C_{\beta_{ij}} \beta_{th_{ij}}$, which gives

$$\beta_{th_{ij}} = \frac{\mu_{yj_{max}} F_{z_{ij}} C_{\beta_{ij}}}{C_{\beta_{ij}}}$$  \hspace{1cm} (16)

but this lead to a slip angle threshold bigger than by using
(15) and the tire will already be in the nonlinear part.

V. SIMULATIONS RESULTS

To evaluate the performance of the proposed algorithm, a
10 DoF vehicle model, simulated in Matlab/Simulink soft-
ware is used in order to simulate the vehicle dynamics. The
model takes into account both the coupling of longitudinal
and lateral slip. The simulation integrates a Pacejka model
for the tire described by [30]. The external disturbances
such as road-bank angle, slope, and aerodynamic forces are
neglected. The estimation was processed for each wheel but
they are both close to the expected values. Finally, Fig.
13 shows the result of slip angle threshold estimation using
(15). When the affine model of the estimation algorithm can
be applied (see Fig. 5), the threshold is hold at a constant
value: it can be assumed that 3 deg. is generally observed for
the limit of the linear region. Then, when the linear model
is no longer valid, i.e. the ratio $p$ is higher than 1.05, the
slip angle threshold is updated with (15) and this value is
hold when $p < 1.05$. We notice in Fig. 13 (magenta dotted
line) that by using (16), the slip angle threshold estimation
is bigger and the tire is already in the nonlinear part while
with (15) the tire has not yet reached the maximum lateral
tire force available (see Fig. 14).

B. Snowy road

The vehicle is moving on the same trajectory as the pre-
vious simulation but at $14 m/s$ on a snowy road such as $\mu =
0.3$. Fig. 11 and Fig. 12 show respectively the results of the
maximum lateral friction coefficient and cornering stiffness
estimations using the estimated and measured lateral forces.
Previous remarks can also be made in this situation. $\mu_{yj_{max}}$

is well estimated in both case and the error of cornering
stiffness estimation is bigger with the estimated lateral force
but they are both close to the expected values. Finally, Fig.
13 shows the result of slip angle threshold estimation using
(15).
Fig. 7. Estimated and measured front left cornering stiffness for wet road

Fig. 8. Measured and estimated lateral force function of slip angle.

Fig. 9. Measured and estimated lateral force function of slip angle and time (black lines delimitate the short period for which the estimation error is important)

All the simulations carried out also revealed that estimating high lateral friction coefficient needs larger slip angles. In contrast, smaller slip angles are needed to have an accurate estimate of lower friction coefficient. Since the slip angle is directly related to lateral maneuvers, larger maneuvers are required to estimate high friction coefficients.

Fig. 10. Estimated $\mu_{\text{max}}$ for wet road

Fig. 11. Estimated $\mu_{\text{max}}$ for snowy road

Fig. 12. Estimated and measured front left cornering stiffness for snowy road

VI. CONCLUSION

This paper developed and investigated a new estimation method for the maximum lateral friction coefficient and the cornering stiffness which will be used in closed loop context in future developments (see [32]). For those estimations a few parameters are needed which are available through Inertial Navigation Systems. It also needs a reliable estimation of lateral tires forces. Detailed experimental results show the performance of the estimation algorithm on different road
conditions. Future works would also consider the comparison of this proposed algorithm to the one developed in [17].

REFERENCES


