Clothoid-Based Speed Profiler and Control for Autonomous Driving

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Abstract—This paper presents a method for optimal speed profile generation in specified clothoid-based paths with known semantic – maximum speed and longitudinal and lateral acceleration – and geometric information. A clothoid can be described using only its kink-points information, i.e. the points defining the start and end of a clothoid. Using the clothoid-based path representation, we formulate the speed profile generation as a convex optimization problem where the objective is to produce a smooth speed that is close to the maximum allowed speed. The vehicle and the road profile define the constraints of the problem. Furthermore, we develop a longitudinal controller by using the speed profiler in a receding-horizon fashion. Thus, we only consider a finite horizon when computing the optimal inputs every sampling time and, in addition, the longitudinal controller also takes into account the newest prediction available from measurements and from the lateral controller. We present a semi-analytical method to generate safe and feasible speed profiles and the tracking of those by the longitudinal controller. We also study the influence of the clothoid-based path representation in the optimality of the obtained solutions. We show that we can get a very good suboptimal speed profile approximation with few more points than the kink-points. In addition, we analyze the influence of an acceleration penalization factor in the smoothness of the speed profile. The higher the acceleration penalization the smoother the speed profile obtained. We show that we can get a very good suboptimal speed profile approximation with few more points than the kink-points. In addition, we analyze the influence of an acceleration penalization factor in the smoothness of the speed profile. The higher the acceleration penalization the smoother the speed profile and the further from the maximum allowed speed is the speed profile.

I. INTRODUCTION

The automotive industry is simmering with new advances in field of autonomous vehicles. All major automotive brands in the field want to have their name written on the world’s history for being the first to launch a fully autonomous commercial car, truck or bus. We have seen incredible advances in this field in the last few years with several autonomous vehicles performing urban driving, platooning and racing [1]–[5].

There is an uncountable amount of work done in the area of trajectory planning and speed control. Velenis et al. have investigated about the optimal velocity profile generation with given acceleration limits [6]–[9]. The authors propose a semi-analytical method to generate optimal velocity profiles on a specified path for a vehicle with given acceleration limitations. The problem of obtaining the optimal velocity profile is formulated as an optimal control problem using a maximum allowed centripetal force as a constraint and solved with the Pontryagin’s Maximum Principle.

In [6], a theoretical analysis with formal proof of optimality of the method is presented for a point mass vehicle. Moreover, in [7], the work was extended to include a half-car model and consequently constraining both front and real axis centripetal forces. Afterwards, in [8], the infinite-horizon optimal control problem was implemented in a receding-horizon fashion. There, a dynamic scheme that determined the planning and execution horizon length was used to guarantee robustness.

Furthermore, within the same idea of minimum-time optimal speed profile, [10] proposes a robot path planning technique for differential drive robots that minimizes the time of reaching an end point with desired heading and velocity. The proposed method involves a generation of a spline that calculates the optimal position of its control points by minimizing the time needed to perform the path. The robot speed is computed using the geometry of the path and constraining the lateral and longitudinal accelerations. Moreover, in [11] the problem of minimum-time optimal speed profile is also addressed but, in this case, a single-track model including tire models and load transfer is considered.

In addition, the strategy is based on the combination of an equivalent formulation of the optimal control problem with a continuation method to find a candidate minimum-time trajectory.

Another active related research is the one considering eco-driving, i.e. preoccupations with fuel consumption in autonomous driving. In [12], the vehicle efficiency is optimized using a dynamic programming approach and the authors claim that applying such method fuel savings up to 16% are possible. Finally, Villagra et al. [13] developed a smooth path and speed planner for an automated public transport vehicle in unstructured environments. In this work, the focus was rather efficiency and comfort than time optimality. Besides producing a smooth path with bounded continuous curvature, the velocity planner uses the semantic information of the road – maximum speed, longitudinal and lateral acceleration, and jerk – and the constraints on the lateral acceleration and jerk to produce comfortable speeds. The results of the proposed strategy were contrasted with real driving maneuvers performed by human drivers in an automated public transport vehicle.

This paper is an extension of [14]. There, we propose a linear time-varying clothoid-based model predictive control for autonomous driving (LTV-MPC). The MPC controller is formulated assuming that a vehicle traveling at low speeds defines a segment of clothoids if the steering angle is chosen to vary piecewise linearly. Hence, the vehicle model used to compute the optimal inputs within a certain horizon is in fact the mathematical equations defining a clothoid. Therefore, we optimize over the clothoid parameters that solve the problem and translate them to vehicle inputs. Furthermore, we propose a path sparsification algorithm that describes a set of waypoints using a set of clothoids described solely by their kink-points.

In this paper, we propose a method for optimal speed profile generation in specified clothoid-based paths with known semantic and geometric information. Furthermore, we translate the speed profile problem to a receding-horizon
problem in order to produce feasible reference speeds that are given to a low-level vehicle speed controller. With our method we do not target time optimal speeds but rather speed feasibility and safety. Our method contrasts with previous work in terms of simplicity, intuition, online processing capability, and tuning. We formulate the speed profile generation as a convex optimization problem where the cost function has two terms and the constraints are given by the vehicle limitations and road geometry. The first term of the cost function is related to the fact that we want to drive as close as possible to the speed limit. This speed limit is defined by the minimum between the maximum speed allowed by law (or user defined) on that road and the maximum speed allowed due to road geometry. The second term of the cost function is used to prevent sudden accelerations. We can choose to penalize more or less the acceleration by regulating one single constant parameter. The goal of the longitudinal controller is to produce feasible speed requests for a low-level controller, such as a cruise controller. Also, it is responsible for tracking the speed profile as precisely as possible by adjusting the speed requests sent to the low-level controller. The controller is formulated in a very similar way as the speed profiler. In this case, we optimize over a finite horizon instead of the full path and we compute the optimal inputs in a receding-horizon fashion every sampling time. This controller is able to get the most recent vehicle behaviour predictions from the lateral controller and sensor information, such that the speed is adapted accordingly.

The rest of this paper is organized as follows: in Section II, we address the optimal speed profile generation by formulating it as a convex optimization problem; in Section III, we introduce the longitudinal controller based on solving the same problem as the speed profiler but in a receding-horizon fashion; in Section IV, we demonstrate the performance of both the speed profiler and the longitudinal controller by using idealistic scenarios and using real path data; finally, in Section V, we provide some concluding remarks and outline future work.

II. CLOTHOID-BASED SPEED PROFILE GENERATION

In this section, we propose a method for clothoid-based speed profile generation by formulating it as an optimization problem.

A. Problem formulation

As proposed in [14], the motivation for using clothoid-based controllers is that the movement of a nonholonomic vehicle at low speeds, i.e. when the lateral dynamics have little influence, can be simply described by clothoids if we limit the steering angle of the vehicle to be a piecewise linearly varying function, i.e. \( \kappa(s) = cs + \kappa(0) \), where \( \kappa(s) \) is the curvature \( \kappa \) as a function of the traveled distance along the path \( s \) and \( c \) is the curvature sharpness. A segment of clothoids described by \( N \) waypoints (or clothoid kink-points) which we use to describe the movement of the vehicle, is mathematically described as

\[
\begin{align*}
    x_{i+1} &= x_i + \int_{s_i}^{s_{i+1}} \cos(\theta + \kappa(s-s_i) + c_{i+1} \frac{(s-s_i)^2}{2}) \, ds \\
    y_{i+1} &= y_i + \int_{s_i}^{s_{i+1}} \sin(\theta + \kappa(s-s_i) + c_{i+1} \frac{(s-s_i)^2}{2}) \, ds \\
    \theta_{i+1} &= \theta_i + \kappa(s_{i+1}) + c_{i+1} \frac{L_i^2}{2} + 1 \\
    \kappa_{i+1} &= \kappa_i + c_{i+1}L_{i+1},
\end{align*}
\]

where \( i = 1, \ldots, N \). Since the vehicle movement is described as a set of clothoids, its state at each kink-point is defined as \( z_i = [x_i, y_i, \theta_i, \kappa_i, c_i] \) where \( x \) and \( y \) are the coordinates of the vehicle in the global coordinate system, and \( \theta \) is the yaw angle and the input is defined as \( u_i = [c_i, L_i] \) where \( c_i \) and \( L_i \) are the \( i \)-th clothoid curvature sharpness (constant by definition) and arc-length respectively and \( s_i \) defines the distance traveled from the beginning of the path until the \( i \)-th kink-point.

The reference path does not include a speed profile to be followed. The speed profiler has the responsibility of generating a feasible speed profile taking into account road regulation, comfort, safety constraints, and vehicle limitations. With this in mind, we formulate the space-domain speed profile generation over the entire path described by \( N \) clothoid kink-points as an optimization problem

\[
\min \sum_{i=1}^{N} (v_i - v_i^{\text{max}}) + \alpha \sum_{i=1}^{N-1} a_i \quad \text{s.t.} \quad \begin{align*}
    a_i &= f(v_{i+1}, v_i, s_{i+1}, s_i), & i = 1, \ldots, N - 1, \\
    a_i &\leq a_{i}^{\text{max}}, & i = 1, \ldots, N - 1, \\
    a_i &\geq a_{i}^{\text{min}}, & i = 1, \ldots, N - 1, \\
    v_i &\geq 0, & i = 1, \ldots, N, \\
    v_i &\leq v_i^{\text{max}}, & i = 1, \ldots, N, \\
    v_1 &\equiv v_{\text{init}}, \\
    v_N &\equiv v_{\text{final}},
\end{align*}
\]

where \( v_i^{\text{max}} \) is the maximum speed that the vehicle can have at the \( i \)-th kink-point, \( a_{i}^{\text{max}} \) and \( a_{i}^{\text{min}} \) are respectively the maximum and minimum acceleration that the vehicle can have at the \( i \)-th kink-point, \( f(\cdot) \) is the function that relates speed with acceleration in space-domain, \( \alpha \) is a constant smoothing term that penalizes accelerations different from zero, and \( v_{\text{init}} \) and \( v_{\text{final}} \) are predefined initial and final speed values respectively. Formulating the speed profiler as a clothoid-based optimization problem we assume that the acceleration is constant between kink-points, making use of the fact that also the curvature sharpness is constant between kink-points.

Throughout the remainder of the paper, the subscripts are used to denote kink-point indices and superscripts to denote extra self-explanatory information. Exceptions should be clear from the context.

Let the speed limit of the road (or user-specified) be \( v_{r}^{\text{law}} \) and the maximum speed due to comfort and safety reasons be \( v_{r}^{\text{road}} \). We can relate \( v_{r}^{\text{road}} \) with the road curvature and banking and with vehicle characteristics such as center of gravity height and mass. In particular, if the road contains the curvature \( \kappa \) information we can relate that with the maximum lateral acceleration \( a_{y} \) allowed and consequently the maximum speed \( v_{r}^{\text{road}} \) allowed on each stretch [15]. Hence, \( v_{r}^{\text{road}} \) can be expressed as
where $a_{\text{v}}^{\text{road}}$ is the maximum allowed lateral acceleration given road and vehicle properties. In [16], a second order transfer function relating the lateral load transfer and lateral acceleration is analytically derived. Thus, if we want to constraint the longitudinal speed using a constant maximum lateral acceleration, then a conservative value has to be chosen to accommodate for the peak resonance of the second-order dynamics.

The maximum speed allowed on the road is

$$v_{i}^{\text{max}} = \min \{ v_{i}^{\text{law}}, v_{\text{l}}^{\text{road}} \}, \quad (4)$$

where $i = 1, \ldots, N$.

Also, we need to derive $f(\cdot)$ in (2b). In continuous-time we know that

$$\frac{dv(t)}{dt} = a(t), \quad (5)$$

but since $v(t) \cdot dt = ds$, assuming that $v(t) \neq 0$ and $v(t)$ is a continuous function, then

$$\frac{dv(s)}{ds} = \frac{a(s)}{v(s)} \quad (6)$$

Integrating both sides of the expression (6) we can represent $a(s)$ as a function of $v(s)$ using a quadratic expression. Thus,

$$\frac{dv(s)}{ds} = \frac{a(s)}{v(s)} \quad (7a)$$

$$\Leftrightarrow v(s)dv = a(s)ds \quad (7b)$$

$$\Rightarrow \int_{s_{i}}^{s_{i+1}} v(s) \, ds = \int_{s_{i}}^{s_{i+1}} a(s) \, ds \quad (7c)$$

$$\Rightarrow v_{i+1}^{2} - v_{i}^{2} = 2(s_{i+1} - s_{i})a_{i} \quad (7d)$$

$$\Rightarrow v_{i+1}^{2} - v_{i}^{2} = 2L_{i}a_{i} \quad (7e)$$

$$\Rightarrow a_{i} = \frac{v_{i+1}^{2} - v_{i}^{2}}{2L_{i}} \quad (7f)$$

where $L_{i}$, as defined earlier, is the distance between two consecutive kink-points. So, the speed description in discrete space is

$$v_{i+1}^{2} = v_{i}^{2} + 2L_{i}a_{i}. \quad (8)$$

We want to solve the problem of fitting the speed profile to the maximum speed allowed and penalize the acceleration changes. Thus, we use $l_{1}$-norm regularization techniques as proposed in [17]. We use the $l_{1}$-norm and not the $l_{2}$-norm since we want the acceleration to be zero most of the time depending on some weighting criteria. We can rewrite the problem (2) in matricial format and minimize with respect to $v_{i}^{2}$ to be compliant with the speed discretization (8) and make a change of variables $w = v_{i}^{2}$

$$\min_{w} ||w - w_{\text{max}}||_{1} + \alpha ||Dw||_{1} \quad (9a)$$

s.t.

$$Dw \leq a^{\text{max}}, \quad (9b)$$

$$Dw \geq a^{\text{min}}, \quad (9c)$$

$$w \geq 0, \quad (9d)$$

$$w \leq w_{\text{max}}, \quad (9e)$$

$$w_{1} = w_{\text{init}}, \quad (9f)$$

$$w_{N} = w_{\text{final}}, \quad (9g)$$

where $\alpha$ is an acceleration penalization factor and $D$ is the matrix operator that calculates first order differences of a vector and includes the distances between waypoints $L_{i}$.

The speed profile generation is done offline and it is used by a longitudinal controller as described in the next section.

### III. Clothoid-Based Longitudinal Controller

In this section, we present a longitudinal controller that uses a very similar formulation as the speed profiler. The longitudinal controller computes speed requests which are given to a low-level speed controller, such as a cruise controller, that is responsible to track them as precisely as possible. In Fig. 1 the proposed system structure is depicted where the controller consists of a decoupled longitudinal and lateral controller. The controller receives inputs from the path sparsification which contains the path described as a set of clothoids as described in [14] and from the speed profile generator. This receives the road information, such as the maximum speed allowed and the road banking $\phi$ together with the curvature information retrieved in the path sparsification. Also, the LTV-MPCC lateral controller, introduced in [14], sends the curvature prediction to be used by the longitudinal controller. The controller outputs a set of requests to the low-level controllers of the vehicle. In particular, the longitudinal controller sends a speed request to the cruise controller and an acceleration request to the brake controller.

The longitudinal controller is formulated similarly to (9). Nevertheless, it works in a receding-horizon fashion and we compute the optimal input for a certain horizon taking into account the speed profile and the predicted curvature given by the lateral controller. The problem is formulated as a tracking problem where we want to minimize the deviations from the reference speed profile and at the same time using the most recent lateral controller predictions to compute a desired speed within the maximum lateral acceleration limits (3). Using the fact that $w = v^{2}$ the controller is formulated as

$$\min_{w_{\text{request}}, \Delta} \|w_{\text{request}} - w_{\text{profile}}\|_{1} + \beta \Delta \quad (10a)$$

$$\begin{align}
Dw_{\text{request}} & \leq a^{\text{max}} \quad (10b) \\
Dw_{\text{request}} & \geq a^{\text{min}} \quad (10c) \\
w_{\text{request}} & \geq 0 \quad (10d) \\
w_{\text{request}} & \leq w_{\text{max}} + \Delta \quad (10e) \\
w_{\text{request}, \ell} & = w_{\text{current}, \ell} \quad (10f) \\
\Delta & \geq 0. \quad (10g)
\end{align}$$

where $w = [w_{1}, w_{2}, \ldots, w_{H}]^{T}$ where $H$ is the prediction horizon. Also, we included a slack variable $\Delta$ to allow the controller to maintain feasibility even if the vehicle speeds over the maximum allowed speed. The weight $\beta$ penalizes how much is the vehicle allowed to overspeed. For example, if the slack variable was not included we could face problem with infeasibility when the vehicle enters a descent and
IV. SIMULATION RESULTS

In this section, we present the main results obtained with the speed profiler and afterwards the longitudinal controller. The simulations were performed using the whole system depicted in Fig. 1 where we simulate the vehicle behaviour using a 4-axles nonlinear bicycle model. Two of the reference paths used are idealistic to assure feasibility of the reference path, eliminate possible sources of errors and provide a proper proof of concept. We also demonstrate the performance of the speed profiler using real data from Scania’s test track in Södertälje, Sweden. All the optimization problems are solved using cvxgen [18]. Moreover, the solver time of both the lateral controller and the longitudinal controller summed indicate their ability to run in a real-time implementation. The solver time of the longitudinal controller is roughly half of the lateral controller [14]. The solver time was evaluated running the controller on a computer with a processor Intel Xeon CPU E5-2670 2.50 GHz with 16GB RAM memory.

A. 4-axles bicycle model

As in [14], the model developed is based on a Scania 480G truck called Astator. For details of the lateral dynamics of the model, we kindly refer the interested reader to [14]. Here, we describe the longitudinal part of the model. For the sake of simplicity, we assumed that the system “cruise controller + vehicle” is a simple first order model and the brake controller can track (negative) accelerations instantaneously. Hence, we can describe the longitudinal part of the model as

\[
\dot{v}_x = \begin{cases} 
A v_{\text{request}} - B v_x, & \text{if } a_f > a_b \\
\text{a}_{\text{request}}, & \text{otherwise}
\end{cases}
\]

(11)

where \(A\) and \(B\) are constants and \(v_{\text{request}}\) and \(a_{\text{request}}\) are inputs.

B. Reference paths

A nominal S-curve reference path was created using clothoids. The desired curvature values and arc-lengths are user-defined.

Previously, we have shown the performance of the lateral controller using only the clothoid kink-points [14]. To increase the accuracy of the controller and to show the performance of the longitudinal controller for different path representation densities we opted for allowing it to use extra points in the path for accuracy reasons. Still, even if we divide each clothoid in extra \(M\) points, we can still argue about the controller accuracy in a sparse representation. An example with 4 extra points per clothoid can be seen in Fig. 2.

Moreover, we use real data from Scania’s test track to compare human driving behaviour with the optimal speed profiler. The Scania’s test track is consisted of two long straights and one sharp U-curve.

C. Speed profiler

Applying the speed profiler (9) to the handmade reference paths with parameters \(a_{\text{max}} = -a_{\text{min}} = 0.5 \text{ m s}^{-2}\), \(v_{\text{law}} = 25 \text{ m s}^{-1}\), \(a_{\text{rad}} = 1.96 \text{ m s}^{-2}\), and \(v_{\text{init}} = v_{\text{final}} = 0\), we obtain the speed profiles shown in Fig. 3 and 4.

In Fig. 3 we used different path densities allowing each clothoid to be divided in \(M\) segments and we used \(\alpha = 0\). The maximum velocity \(v_{\text{max}}\) is represented using the maximum path representation density possible. We intend to analyze the suboptimality properties of the speed profile obtained when the path representation is sparser. We assume that the optimal speed profile in these cases occurs when we use maximum path representation density possible. We can see that, except when the path is too sparse, the speed profile is not very different when compared to the optimal solution. Actually, note that with \(M = 5\), the speed profile is already very similar with the optimum one and in the straight lines the path has waypoints spaced more than 30 m. We conclude that the speed profile can handle a sparse path representation and give suboptimal feasible speed references.
In Fig. 4 we fixed $M = 5$ and varied $\alpha$. The purpose of this is to study the influence of the penalization factor $\alpha$ in the speed profile. In this case, we do not analyze optimality but smoothness. We clearly see that the bigger the acceleration penalization, the smoother the speed profile is. An interesting result is that, for $\alpha = 12$ the speed profile is such that it only changes speed before and after the curve, i.e. there is no acceleration when entering or exiting a curve.

Finally, we compare the speed used by a human driver in one Scania’s test track lap with the optimal speed profile. In this case, for the sake of comparison, we used $a_{\text{max}} = -a_{\text{min}} = 0.3 \text{ m s}^{-2}$, $v_{\text{law}} = 13 \text{ m s}^{-1}$, $a_{\text{road}} = 1.96 \text{ m s}^{-2}$, and \(v_{\text{init}} = v_{\text{final}} = 0\). It is possible to see in Fig. 5 that the speed profile is similar to the speed used by the human driver. This means that the speed profiler provides feasible speed profiles that human drivers understand as safe and comfortable speeds. The largest deviations happened around 1250 m and 2100 m. In the first point, the vehicle faces a steep uphill and cannot maintain the speed. In the second point, the vehicle faces a downhill and the driver opted to let the vehicle gain speed without breaking.

D. Longitudinal Controller

The purpose of the longitudinal controller is to provide a
speed or acceleration request to the cruise controller or brake controller of the vehicle such that it tracks the speed profile computed offline. The longitudinal controller computes an optimal speed or acceleration request over a certain horizon and it takes into account the curvature predictions made by the lateral controller. For example, in case of an unexpected event, the vehicle may need to avoid an obstacle making a very sharp turn and in this case the speed request would be significantly reduced since the predicted curvature requests are very high. We tested the longitudinal controller in the nominal S-curve to evaluate its performance. In Fig. 6 the performance of the longitudinal controller is depicted. The speed profiler parameters were chosen as $a_{\text{max}} = a_{\text{min}} = 0.75 \text{ m s}^{-2}$, $v_{\text{law}} = 25 \text{ m s}^{-1}$, $a_{\text{rad}} = 1.96 \text{ m s}^{-2}$, $v_{\text{limit}} = v_{\text{final}} = 0$, and $\beta = 0$. Also, the every clothoid segment was divided in $M = 5$ segments, i.e. with 4 extra points. The controller parameters were chosen as $a_{\text{max}} = a_{\text{min}} = 1 \text{ m s}^{-2}$, $v_{\text{law}} = 25 \text{ m s}^{-1}$, $a_{\text{rad}} = 1.96 \text{ m s}^{-2}$, and $\beta = 5$. We can see that the vehicle smoothly and precisely tracks the speed profile by applying the cruise control or the brakes when needed. Also, the speed request is given ahead of time to allow the cruise controller to reach the set speed.

In the beginning of the simulation, a step speed request is given to the vehicle since very low speed request would result in erratic behaviour of the longitudinal controller and noisy vehicle curvature predictions prejudicial for the lateral controller. In the end of the simulation, a constant low speed is requested to the vehicle until it is in the neighborhood of the last point where the reference speed is zero.

V. CONCLUSIONS

In this paper, we presented a method to generate optimal speed profiles in a given clothoid-based path with given vehicle and road constraints. The generation of an optimal speed profile is formulated as a convex optimization problem where we minimize the deviations between the speed profile and the maximum speed allowed on the road. The maximum speed allowed on the road has two components, one regarding the maximum speed allowed by law (or user defined) and the second considers safety issues by taking into account the road geometry. Also, the speed profile can be tuned in order to produce more or less smooth speed profiles with respect to the changes in acceleration. Furthermore, we have developed a longitudinal controller which works in a receding-horizon fashion by solving a very similar problem as the speed profiler. In this case, the longitudinal controller only takes into account a finite horizon ahead of the vehicle and receives the most updated vehicle state predictions. This way, the longitudinal controller produces feasible and safe speed requests for the low-level speed controller. We analyzed the influence of different path description densities and the influence of the acceleration penalization factor in the speed profile generation. We assumed that the optimal speed profile is the one using the densest path description. We concluded that the sparser the path description is, the further away the resultant speed is from the optimal. However, we could see that the path description does not need to be very dense in order to achieve a good sub-optimal solution with the benefit of being able to produce it faster. Also, by varying the acceleration penalization factor we could modify the smoothness of the speed profile. In this case, we have a clear trade-off between an aggressive speed profile which tends to deviate as little as possible from the maximum speed allowed, or a smoother speed profile that is less aggressive but is does not drive at the speed limits. We also compared the speed profile generated by Scania’s test track with a human driver speed profile, and showed that they are very similar proving that such speed profile is feasible and comfortable. Simulations, using a simplified first-order cruise controller model, show that the longitudinal controller works well by sending correct speed or acceleration requests. As future work, we should consider situations that include road banking and slope. In those, we can extend our work by formulating the problem in terms of energy or fuel efficiency. Also, we should consider investigating the introduction of speed-dependent constraints, i.e. the lateral acceleration limits vary with the longitudinal speed of the vehicle. Naturally, the proposed method should be implemented and validated on a real vehicle.

REFERENCES