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Preliminary study for motion sickness reduction in autonomous vehicles: an MPC approach

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Abstract

This study shows a new method for evaluating the optimal speed profile for a given route. The article deals with the feasibility of autonomous driving (AD) strategies that take into account passenger comfort, focusing on the motion sickness (MS) phenomenon. In this paper a Non-linear Model Predictive Control (NMPC) approach is used to model a vehicle moving along a predefined route; the vehicle is modelled using a point mass model and is assumed to move along a spline. Literature models are used to model MS. The Model Predictive Control (MPC) used is non-linear because the model of this article is integrated in the space domain instead of a traditional integration in the time domain; this approach is shown in several papers concerning autonomous driving control. The main contribution of this study is to implement quantitatively the consideration of comfort in autonomous driving. In the literature, the articles related to comfort in AD address the problem in a qualitative way and those related to AD control techniques analyse the problem considering only the vehicle dynamics. Another contribution is to present the spatial transformation of MS models in the literature, allowing an easier implementation of these models in AD control. The results of this introductory analysis show how MS can be reduced by minimizing the increase in travel times. This technique can be used in AD or advanced driving assistance systems (ADAS) to create less nauseogenic systems or can also be used in traditional driving by advising the human driver with the best speed profile to reduce MS.

Keywords: Motion sickness; Nonlinear model predictive control; Vehicle comfort; Vehicle control; Passenger modelling; Car sickness; Subjective vertical conflict theory

1. Introduction

Autonomous driving (AD) is a disruptive technology in the automotive industry and in vehicle research: it is considered as a great opportunity for increasing safety and trying to fulfil the EU target for road casualties, as in

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Adminaité-Fodor et al. (2019) is shown that since 2014 the EU is not compliant with its path to reduce of 50% road fatalities within 2020.

However to have such a big impact AD has to be widespread and has to be as accepted as possible by the road users; to be pleasant to most of the road users, it has to be comfortable, which can be turned in being less discomfortable as possible; one of the main causes of discomfort in AD can be found in motion sickness (MS): the lack of control by the driver can lead to greater MS than normal vehicles and in literature (e.g. in Sivak and Schoettle (2015)) is shown how MS can be important in autonomous cars.

The proposed countermeasures in literature are all concerned in vehicle design (e.g. head-up displays), postural and behavioural countermeasures; however in this paper will be analysed if it is possible to control the vehicle in a way that combine minimum travel time and low levels of MS, presenting an innovative real-time feasible MS aware control for autonomous vehicles.

Nomenclature

ρ	curvature
a_n	lateral acceleration
a_t	longitudinal acceleration
b	Hill function parameter
c	perception conflict
C_{MS}	motion sickness cost
C_u	input cost
C_v	velocity cost
c_x	longitudinal perception conflict
c_y	lateral perception conflict
c_z	vertical perception conflict
g	gravitational acceleration
g	instantaneous disturb
j_t	longitudinal jerk
n	Hill function exponent
s	space
t	time
u	system input
u_{lb}	input lower bound
u_{ub}	input upper bound
v_{max}	maximum longitudinal velocity
v_t	longitudinal velocity
X	state vector
x	x road coordinate
y	y road coordinate
AD	autonomous driving
ADAS	advanced driving assistance systems
MPC	model predictive control
MS	motion sickness
MSI	motion sickness incidence
NMPC	nonlinear model predictive control
SQP	sequential quadratic programming

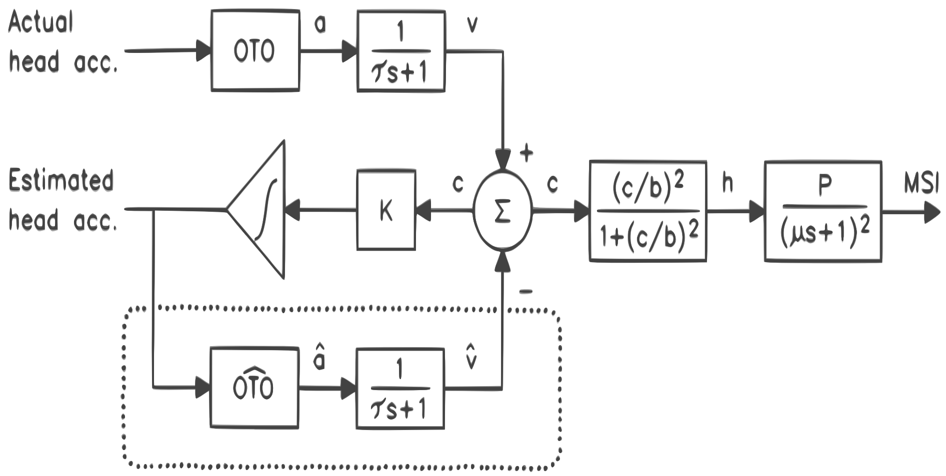

Fig. 1: Bos and Bles model

2. State of Art

2.1. Motion sickness

The main theory describing MS is the sensory conflict theory described by Reason and Brand (1975): the conflict between the motion perceived by the vestibular system, the one perceived by the visual system and the one expected from the previous experiences lead to motion sickness. The conflict deceives the brain into thinking that it is intoxicated, so the body begins its defensive strategy increasing parasympathetic activity eventually leading to emesys if the stimulus is strong and long enough.

To investigate the most provocative frequencies several experimental campaign were made; one of the most important is from O'Hanlon and McCauley (1973): it shows how the frequencies of the MS phenomenon are from 0.1 to 1Hz with a peak of incidence of MS around 0.17Hz.

To estimate the level of MS from the accelerations, several numerical models are proposed in the literature, tuned using these experimental campaigns; the main ones are:

- **Lawther and Griffin (1987):** an extension of the whole body vibration models suitable for MS assessment; it serves as the base of the ISO, 2631-1:1997, the current ISO standard related to MS.
- **Bos and Bles (1998):** a theoretical model suitable for vertical motion.
- **Braccesi and Cianetti (2011):** a 3-D extension of the Bos and Bles model called *UniPG model*.

Despite the significance of the ISO standard, Braccesi and Cianetti show some significant drawbacks of the Griffin model: mainly the fact that the Motion Sickness Incidence (MSI) (the percentage of people tha can vomit due to the motion) can never drop since it is an integral of an always positive value; when dealing with long travels the provocative input is not constant and straight parts can significantly drop the MSI generated in more winding section of the path: such model can not represent this drop of MSI. This is the main reason why the Griffin model were dropped by the authors of this paper in favour of the UniPG model.

To fully understand the UniPG model is useful to take a quick look of the Bos and Bles one: the acceleration at the head are filtered by a transfer function modelling the perception of the vestibular system, after that a conflict c is computed using the difference between the perceived and expected acceleration; the conflict is passed into an Hill function to create an instantaneous disturb h and, by means of a transfer function, its finally used to obtain the MSI.

The UniPG model takes the three components of the head acceleration and creates three conflicts, the instantaneous disturb is computed using the modulus of the conflict vector. One of the versions of this model is capable of modelling the effect of the visual input of the subject implementing the work of Telban and Cardullo (2001); since the main focus of this paper is to evaluate the feasibility of a quantitative approach to MS reduction in autonomous vehicles, the mathematical complexity of the formulation of the visual-vestibular interaction is considered excessive and, therefore, neglected.

2.2. Autonomous Driving

Control of autonomous vehicles consists of three main tasks:

1. Perception of the environment
2. Trajectory planning
3. Path following

This paper present a model suitable for being implemented in a path following hierarchical control system using a simplified model such as the one presented by Liniger and Lygeros (2019); Novi et al. (2019). The idea behind the hierarchical controllers is to create a simple model with a long prediction horizon and more accurate levels with smaller horizons to be able to fulfil the real-time requirements. Since the MS frequencies are very low, the idea is to create a very simple model of the vehicle capable of mitigating the MS to eventually combine it with a more accurate control.

Since the path following task is a control of a nonlinear system evolving in time subject to constraints a popular control technique is the use of predictive control. This can be done using linearised model of the vehicle like Falcone et al. (2007) or nonlinear ones like the one used by Liniger and Lygeros (2019), depending on the performance and accuracy required. Since the constraints are often space-dependant (e.g. track limits) and the time is also an interesting objective function for such controllers Gao et al. (2012) proposed a space transformation: defining the system as space-dependant the time can be explicitly formulated, hence enabling its use as an objective function.

3. Motion sickness aware vehicle model

The main idea behind the presented paper is to exploit the structure of the control systems used in autonomous driving to optimize the speed profile of the vehicle to reduce the MS while reducing the travel time. The MPC controls define a cost function and optimize the input to the vehicle to minimize the cost without constraints violation; in the literature such functions are strictly related to the vehicle dynamics (e.g. minimize the travel time, reduce the acceleration, etc.), however defining what means for a vehicle to behave *well* is not as straightforward as it might seems. In the present paper the cost function combines the minimization of the travel time and the reduction of the instantaneous disturb as defined in the UniPG model.

Since the model presented is intended to be integrated within a hierarchical control system, it is intended to be as simple as possible and to run in real time while defining a speed profile that can be used as an upper limit in a lower level control; this speed profile is an *optimal* trade off between minimum travel time and minimum MSI.

The model presented is a point mass model constrained on a spline representing the road; the model is defined as space-dependant, this give the advantage that the road curvature is not varying during the optimization of the system and it is consistent to similar approaches in low-level controls in the literature. The drawback of the space-dependant formulation is that even a simple model like the one used in this paper is defined as a non-linear model.

3.1. Point mass dynamics

Since the vehicle model is a simple point-mass moving on a spline, the dynamics is straightforward and can be described by the following equations:

$$\begin{cases} \dot{v}_t = a_t \\ \dot{a}_t = j_t \end{cases} \tag{1}$$

Table 1: *head acceleration → conflict* state space coefficients

a_{11}	a_{12}	a_{13}	a_{21}	a_{32}	b_1	c_1
−3.33	−4.18	−2.33	1	1	2.36	3.93

where v_t, a_t and j_t are the longitudinal velocity, acceleration and jerk. The jerk is used as the system input and it is constrained to $\pm 3ms^{-3}$; this is done to obtain a more realistic acceleration profile preventing unrealistic variation between simulation steps.

The lateral acceleration is computed using the path curvature ρ using the following equation:

$$a_n = \rho v_t^2 \tag{2}$$

Such model has been intended for everyday driving on public roads,therefore the authors imposed a maximum acceleration of 0.3g, since the lateral acceleration is not an actual state, the constraint equation is:

$$\sqrt{a_t^2 + a_n^2} = \sqrt{a_t^2 + \left(\rho v_t^2\right)^2} \leq 0.3g \Rightarrow a_t^2 + \left(\rho v_t^2\right)^2 - (0.3g)^2 \leq 0 \tag{3}$$

where g is the acceleration of gravity.

For the modelling of the curvature a lookup-table has been used.

3.2. Motion sickness model

For the modelling of MS the UniPG model has been used; to implement it within the MPC solved using *fmincon* the following steps are carried out:

1. the *perceived acceleration → conflict* closed loop transfer function for the definition of the conflict has been calculated
2. the *head acceleration → conflict* transfer function has been obtained from the series of the one obtained in the previous step and the one modelling the response of the vestibular system
3. the previous step transfer function as well as the *instantaneous disturb → MSI* one have been transformed to state-space representation

In this paper the vertical motion is neglected, therefore only x,y directions of the UniPG model are computed; since the longitudinal and lateral directions have the same coefficients the *head acceleration → conflict* state space for each direction is described in equation 4 with the coefficients summarized in table 1:

$$\begin{gathered} A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & 0 & 0 \\ 0 & a_{32} & 0 \end{bmatrix} B = \begin{bmatrix} b_1 \\ 0 \\ 0 \end{bmatrix} \\ C = \begin{bmatrix} c_1 & c_2 & 0 \end{bmatrix} \qquad D = 0 \end{gathered} \tag{4}$$

Table 2: *instantaneous disturb → MSI* state space coefficients

a_{11}	a_{12}	a_{21}	b_1	c_2
$-2.22 \cdot 10^{-3}$	$-1.23 \cdot 10^{-6}$	1	1	$1.05 \cdot 10^{-4}$

For the definition of the Hill function, since $n = 2$, a simple formulation can be obtained:

$$h = \frac{\left(\frac{||c||}{b}\right)^n}{1 + \left(\frac{||c||}{b}\right)^n} \xrightarrow{n=2} h = \frac{c_x^2 + c_y^2 + c_z^2}{b^2 + c_x^2 + c_y^2 + c_z^2} \xrightarrow{c_z=0} h = \frac{c_x^2 + c_y^2}{b^2 + c_x^2 + c_y^2} \tag{5}$$

The *instantaneous disturb → MSI* state space is described in equation 6 with the coefficients summarized in table 2:

$$\begin{gathered} A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & 0 \end{bmatrix} \; B = \begin{bmatrix} b_1 \\ 0 \end{bmatrix} \\ C = \begin{bmatrix} 0 & c_2 \end{bmatrix} \quad D = 0 \end{gathered} \tag{6}$$

3.3. Assembling the model

The entire model can be obtained by assembling the presented sub-module for the point-mass dynamics, two sub-modules for lateral and longitudinal conflicts and one sub-module for the MSI. The input for the longitudinal conflict c_x submodule is the longitudinal acceleration and for the lateral conflict c_y it is the lateral acceleration as defined in equation 2; the two conflicts are used to obtain the instantaneous disturb h as per equation 5 which is the input to the model defined in 6, defining the MSI.

3.4. Space transformation

To obtain good performance during the optimization it is necessary to define the Jacobian of the system and constraint equations; since the curvature of the road is obviously a space-dependant parameter, if the model had been time-integrated, it would have been necessary to define the Jacobian of the curvature lookup table, while defining it as a space-integrated model such step is no longer needed; another advantage is that in more complex models path constraints (e.g. track width) are space-dependant and space-transformation is a valid strategy to handle such constraints as well as have time as an explicit cost function as shown by Gao et al. (2012); Novi et al. (2019), so such transformation is more consistent with eventual lower level controls.

Such transformation for a simple model like the one presented is fairly straightforward and it is described by equation 7:

$$x' = \dot{x}\frac{\mathrm{d}t}{\mathrm{d}s} \text{ where } x' = \frac{\mathrm{d}x}{\mathrm{d}s} \tag{7}$$

For the presented model the implication of such transformation is that each equation described in the previous paragraphs has to be divided by v_t, hence the model is a non-linear model and the optimization has to be done with nonlinear solvers like the sequential quadratic programming (SQP) solver *fmincon*. As an example, equation 1 when space transformed becomes:

$$\begin{cases} v_t' = \dfrac{a_t}{v_t} \\ a_t' = \dfrac{j_t}{v_t} \end{cases} \tag{8}$$

3.5. Cost function

The aim of the model is to minimize the time spent to travel while preventing motion sickness; to assess the reduction of MS the authors choose to keep the MSI below a certain level; since the MSI is defined as the percentage of people that get sick, the authors chose to keep it below 20%, so that in a five passenger car it is unlikely that someone get sick. The MS aware model is compared with a minimum time model subject to identical constraints.

So the minimum time objective function has the following definition due to the spatial transformation:

$$\min \int_{s_0}^{s_f} t(\xi)\ \mathrm{d}\xi = \min \int_{s_0}^{s_f} \frac{1}{\dot{s}(\xi)}\ \mathrm{d}\xi \tag{9}$$

Where s_0 and s_f are the start and finish position. Since the model is constrained on the spline ($v_n = 0$), and equation 9 further simplifies into equation 10:

$$\min \int_{s_0}^{s_f} \frac{1}{v_t(\xi)}\ \mathrm{d}\xi \tag{10}$$

Due to the discretization the base model can be summarized in the following equation:

$$\begin{gathered} \min_{X,u}\ \sum_{k=1}^{N_h} \left(C_v \frac{1}{v_{t_k}} + C_u u_{k-1}^2 \right) \\ \text{subject to:} \\ X_0 = X(0) \\ X_{k+1} = f(X_k, u_k) \\ 0 < v_{t_k} \leq v_{max} \\ u_{lb} \leq u_k \leq u_{ub} \\ a_t^2 + \left(\rho v_t^2\right)^2 - (0.3g)^2 \leq 0 \end{gathered} \tag{11}$$

where C_v is the weight on time, C_u is the weight on the input $\mathbf{X} = [X_1, X_2, \ldots, X_{N_h}]$, $\mathbf{u} = [u_0, u_1, \ldots, u_{N_h-1}]$, f are the dynamics equations described previously, v_{max} is defined as the maximum legal speed, u_{lb} and u_{lb} are the lower and upper bounds on the longitudinal jerk as defined in paragraph 3.1.

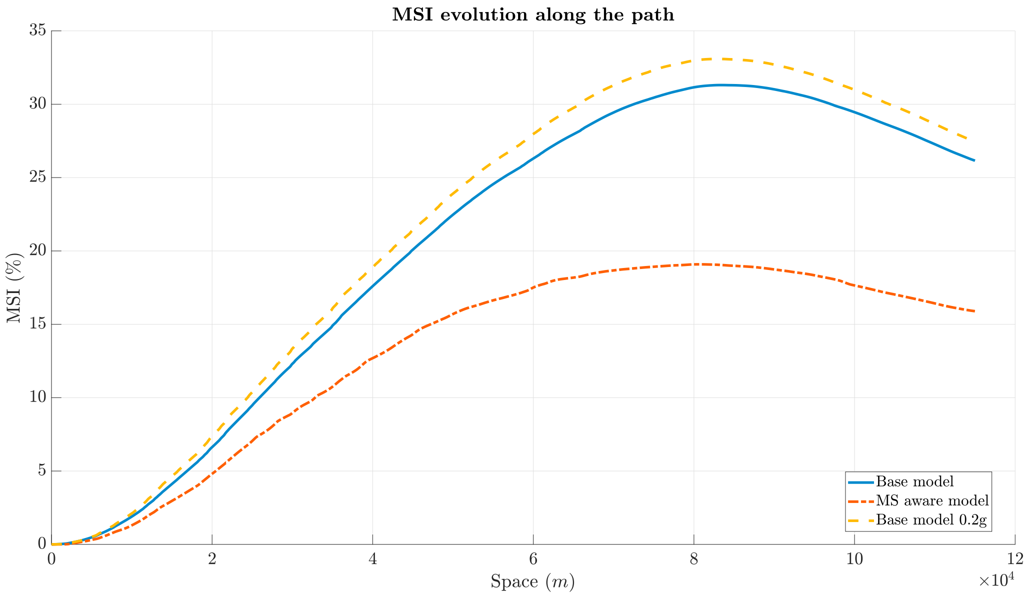

Fig. 2: Evolution of MSI along the test path

The MS aware model cost function takes the instantaneous disturb h and uses it in a cost function similar to the one of equation 11:

$$\min_{X,u} \sum_{k=1}^{N_h} \left(C_v \frac{1}{v_{t_k}} + C_u u_{k-1}^2 + C_{MS} h_k \right) \tag{12}$$

where C_{MS} is the weight for the MS part of the cost function; the constraints are the same as in equation 11.

4. Results

To evaluate the capabilites of the presented model, it is simulated during 116 km highway driving and compared with the base model to evaluate the MS reduction.

4.1. Path definition

For the path definition the authors compared several different sites to extract a .gpx describing the path. The sites analysed are:

- Strava
- Open Source Routing Machine (OSRM)
- Google Maps
- Google Earth

The authors used Google Earth to extract the .gpx, since it is one with the highest number of waypoints and it is easy to use. The speed limits are available only under subscription to *Google Roads API*, however, due to the exploratory

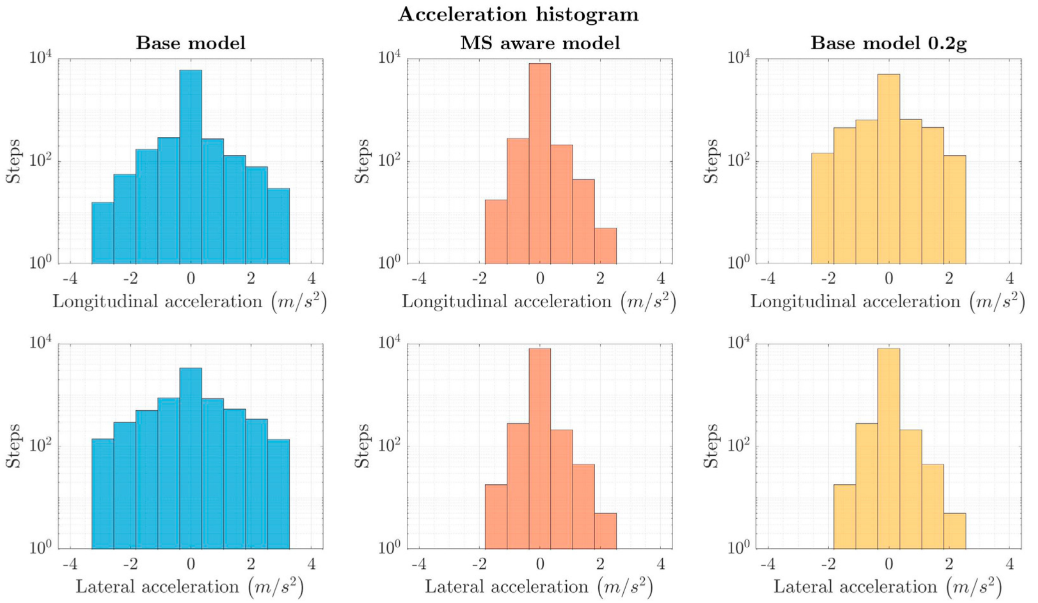

Fig. 3: Acceleration histogram plot

nature of this paper the authors decided to use a constant limit of 120 km/h; even if the speed limits are not the real one, this does not change the results obtained with this study.

With the .gpx file the authors have *Latitude-Longitude-Altitude* coordinates that are converted by the authors in a *North-East Down* representation. With a NED representation the waypoints are mapped in an $(x; y)$ grid; a spline can be easily fitted through the waypoints and the curvature computed using equation 13:

$$\rho = \frac{|x'y'' - x''y'|}{(x'^2 + y'^2)^{\frac{3}{2}}} \tag{13}$$

the resulting curvature is used to create a lookup table used to evaluate the lateral acceleration.

4.2. Base model results

The base model run in $13' : 22''$ and the simulated time is $58' : 58''$ with a peak in the MSI of 31.3%; therefore the model is faster than real time even with non-normalized states and cost function and using *fmincon* as solver.

Accelerations fulfill the constraints as can be seen in figure 3.

4.3. MS aware model results

The presented model run in $43' : 12''$ and the simulated time is $1 : 12'03''$ with a peak in the MSI of 19.1%; therefore the model is still faster than real time even with non-normalized states and cost function and using the SQP solver *fmincon*.

The smaller acceleration is not a simple reduction of the size of the constraint circle, but depends on the effectiveness on reducing the MSI: to demonstrate it a base model is simulated binding the maximum acceleration to $0.2g$ and the maximum MSI is even higher than the base model as can be seen in figure 2; this can be explained by looking at figure 3: the accelerations are lower in modulus, but the vehicle spends more steps accelerating, therefore the MSI is higher.

5. Conclusion and outlook

The presented model introduces a new way of accounting for passengers comfort in AD; until now the vehicle control focuses only on vehicle performance to allow for faster and safer vehicles, however in the next years AD will be mature enough to allows for long highway trips to be done fully autonomously, therefore there will be new demands for better passenger comfort in AD. In the paper is presented a first quantitative approach to MS reduction during AD. The main contribute is the definition of a quantitative approach since, until now, qualitative approaches like in Diels et al. (2016) in the literature are present, while quantitative ones are rare and no one approach the issue of controlling the vehicle.

A minor contribute is the space transformed implementation of the UniPG model allowing for MS aware space dependant controls instead of time dependant ones.

The presented paper introduces the possibility of a comfort oriented optimal control in AD; following research activities will explore the effect of path definition and body dynamics for MS arousal in autonomous vehicles, with similar techniques.

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