Impact of Lateral Acceleration on Motion Sickness in Automated Driving

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Abstract: This paper demonstrates the potential of implementing the lateral Motion Sickness Dose Value (MSDV) model in motion planning to reduce motion sickness in automated vehicles. In our study, we evaluate motion sickness ratings of participants experiencing two different trajectories: a *standard* trajectory, with larger lateral accelerations, and a *comfort* trajectory, with reduced lateral accelerations. We fit the MSDV model to the motion sickness ratings of passengers who experienced the *standard* trajectory and use this fitted model to assess the *comfort* trajectory regarding motion sickness. A comparison of this MSDV model-based assessment with the passenger's motion sickness ratings of the *comfort* trajectory shows that a comparable fit with minimal loss in accuracy is achieved. Thus, our study demonstrates that the MSDV model can be used to predict motion sickness symptoms. These findings highlight the potential of utilizing the MSDV model in trajectory planning, as a reduced MSDV correlates with reduced passenger symptoms.

Keywords: Motion sickness, MSDV model, motion comfort, trajectory planning

1 Introduction

Automated vehicles have the potential to transform mobility, offering enhanced safety, energy efficiency, and comfort. However, motion sickness encountered in automated vehicles may hinder the broad adoption of automated vehicles due to the discomfort resulting from related symptoms such as nausea, dizziness, and sweating [1]. In [2], the authors report that 6 % to 10 % of passengers riding in self-driving vehicles often or always experience some level of motion sickness. This high occurrence of motion sickness is a potential barrier to the acceptance of automated driving functions and self-driving vehicles. Paradoxically, a central promise of automated vehicles contributes to this issue: freeing passengers from the task of driving to focus on different activities, such as working or relaxing. The shift in focus away from perceiving the vehicle's motions is the main contributing factor to motion sickness [1]. Whereas this phenomenon can also occur when riding as a passenger in a vehicle driven by a human, it is hypothesized that the driver of a vehicle acts as a *motion sickness predictor* and tends to drive such that motion sickness is minimized [3]. This natural motion sickness mitigation is not present in automated vehicles, and thus, it is essential to integrate insights from research on motion sickness into the motion generation of automated vehicles [4].

In the vehicle automation architecture, motion planning holds the greatest potential for minimizing motion sickness alongside route planning that can avoid roads that might induce motion sickness [5]. The main objective of motion planning is to ensure that the resulting reference trajectory is dynamically feasible and collision-free within a given planning horizon [6]. In addition, motion planning provides the flexibility to optimize for secondary objectives

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that require a considerable prediction horizon, such as motion sickness. This flexibility allows for planning collision-free trajectories that additionally minimize motion sickness [5].

A motion sickness model is needed to optimize for motion sickness within the planning horizon of motion planning. A motion sickness model does not necessarily need to predict the susceptibility of an individual person to motion sickness. However, the input-output behavior of a motion sickness model should at least represent how potential motion sickness triggers that are common to various persons affect their motion sickness susceptibility. With such a model, the planner has the potential to mitigate the related motion sickness triggers by minimizing the motion sickness that the employed model predicts.

The contribution of this work is to demonstrate that the investigated motion sickness model offers the capability of representing the effect of motion sickness triggers on the motion sickness susceptibility of various persons.

The outline of this paper is as follows. In Section 2, different motion sickness models are presented and compared, and a model is selected for investigation in a study. In Section 3 we present the design of the study. The results of the study are presented and discussed in Section 4.

2 Motion Sickness Models

There are two different approaches for describing motion sickness that are commonly used: conflict theory and the concept of frequency-based stimuli. According to conflict theory, motion sickness results from a sensory conflict between inputs provided by the visual, vestibular, and proprioceptive systems of the human body [7]. To unify various types of motion sickness resulting from conflicting sensory inputs, the subjective vertical conflict (SVC) theory suggests that motion sickness arises if a vertical that is perceived by sense organs is in conflict with the subjective vertical that is determined based on previous experiences [8]. The SVC theory is the basis for the widely-used six degrees of freedom (6DOF)-SVC model presented in [9], which predicts the motion sickness incidence (MSI). The MSI describes the share of individuals vomiting under specific motion conditions [10]. The 6DOF-SVC model predicts the MSI by considering three-dimensional movements, which makes it suitable for modeling motion sickness in (automated) driving. The MSI is adapted in current research, as it cannot represent subjective and mild symptoms [11].

The SVC model is still an active research area [12]. It is based on a white-box approach and aims to describe the relationship between conflicting sensory perceptions contributing to motion sickness. The SVC model models motion sickness based on the acceleration of the passenger's head. This data can be measured in laboratory studies using head-mounted acceleration sensors, and thus, the SVC model is useful for understanding and describing motion sickness. However, using the acceleration of the passenger's head makes it particularly challenging to integrate the model into motion planning, as this requires an additional head and body model that maps the vehicle acceleration to the acceleration of the passenger's head [13], [14], [15]. In addition, it is challenging to parametrize the SVC model due to its large number of parameters, and there is no assurance that the model will avoid generalization errors if applied to new scenarios.

In contrast to the conflict theory, the frequency-based concept of describing motion sickness assumes that repeated exposure to motion stimuli accumulates a *dose* that results in motion sickness symptoms. Based on this, the authors in [16] develop the Motion Sickness Dose Value (MSDV) model that is used in the international standard for evaluating human exposure to whole-body vibrations [17]. The authors in [18] call for considering vibrations in the longitudinal (x), lateral (y), and vertical (z) direction for describing motion sickness, which results in the following representation of the MSDV model:

$$\mathrm{MSDV} = \sqrt{\sum_{i=\{\mathrm{x},\mathrm{y},\mathrm{z}\}} \left(K_i \int_0^T \left(a_{i,\mathrm{w}}\left(t\right)\right)^2 \mathrm{d}t \right)}, \tag{1}$$

in which K_i is a weighting factor that indicates the impact of the accumulated, frequency-weighted longitudinal, lateral, and vertical acceleration

$$a_{i,\mathrm{w}}(t) = a_i(t) * W_i, \tag{2}$$

$i \in \{\mathrm{x}, \mathrm{y}, \mathrm{z}\}$ on the MSDV. The operator $*$ represents the convolution operator. Figure 1 depicts the transfer functions of the frequency weights W_x and W_y used in [19] and [20].

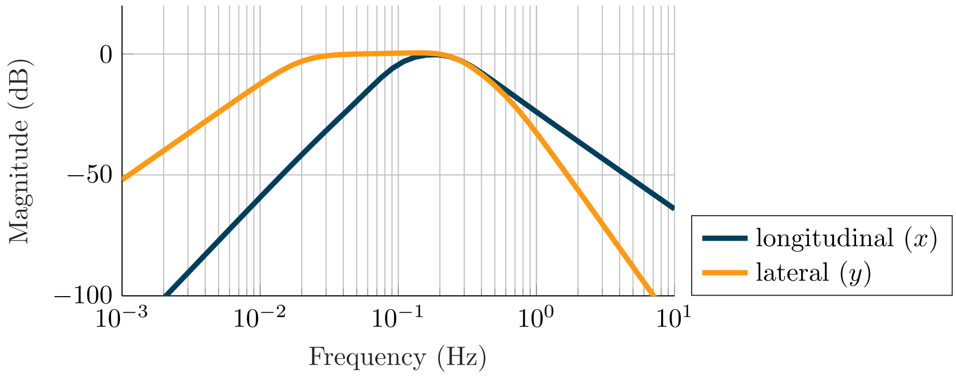

Figure 1: Transfer functions of frequency weights for longitudinal and lateral acceleration are depicted, as defined in (2).

The MSDV model is an empirical model that relies on fitting transfer functions to the frequency behavior of data collected in studies. Thus, the model is classified as a black-box model. Nevertheless, it is interpretable and easy to adjust, which makes it the state of the art in research that is associated with integrating motion sickness models into motion planning.

We choose to investigate the MSDV model in our study due to its simplicity for being implemented in motion planning. This complies with the results of [5], [21], [22] that demonstrate that using the MSDV model in motion planning to reduce the MSDV value of reference trajectories works well in simulation. These promising results and the simplicity of the MSDV call for evaluating whether the reduction of the MSDV value translates into an improvement in passenger motion sickness ratings. Previous studies show that the MSDV model is effective in modeling experienced mean motion sickness in vehicles for specific scenarios [23]. However, it has not yet been studied how varying the maximum used acceleration impacts the severity of passengers' experienced motion sickness.

3 Study Design

The presented study aims to compare two different acceleration profiles w.r.t. their effect on the motion sickness experienced by the participants. For this, the participants are separated into two groups, each assigned to an acceleration profile. Within a group, all participants experience the same acceleration profile, defined by a reference trajectory that is tracked by an automated vehicle.

The testing ground used for the study is located at the Schaeffler Hub for Advanced Research (SHARE) at the Karlsruhe Institute of Technology (KIT). We designed a closed circuit reference path with a total length of 614 m that fits on the testing ground. The reference path, depicted in

Figure 2: The reference path that is used in the presented study is depicted in orange.

Figure 2, is designed to simulate common driving maneuvers associated with motion sickness, such as roundabouts and hairpin turns. In addition, extended straight sections that allow for high longitudinal accelerations are integrated. The closed-circuit design enables repeated driving, which makes it ideal for comprehensive studies.

Two reference trajectories that both follow the reference path depicted in Figure 2 but which differ in their acceleration profiles are used in the study. The reference trajectory that features a gentle acceleration profile is referred to as *comfort* trajectory, and the trajectory that features an ambitious acceleration profile is referred to as *standard* trajectory. The parameters used for planning the trajectories are presented in Table 1. The resulting acceleration profiles of both trajectories of one lap are depicted in Figure 3.

Table 1: Parameters used for planning the *comfort* trajectory and the *standard* trajectory.

Parameter	***Comfort* Trajectory**	***Standard* Trajectory**
Target velocity v_x	$10\,\mathrm{m\,s^{-1}}$	$10\,\mathrm{m\,s^{-1}}$
Longitudinal acceleration limit $a_{\mathrm{x,max}}$	$3\,\mathrm{m\,s^{-2}}$	$3\,\mathrm{m\,s^{-2}}$
Lateral acceleration limit $a_{\mathrm{y,max}}$	$2.55\,\mathrm{m\,s^{-2}}$	$5.25\,\mathrm{m\,s^{-2}}$
Longitudinal jerk limit $j_{\mathrm{x,max}}$	$0.3\,\mathrm{m\,s^{-3}}$	$0.8\,\mathrm{m\,s^{-3}}$

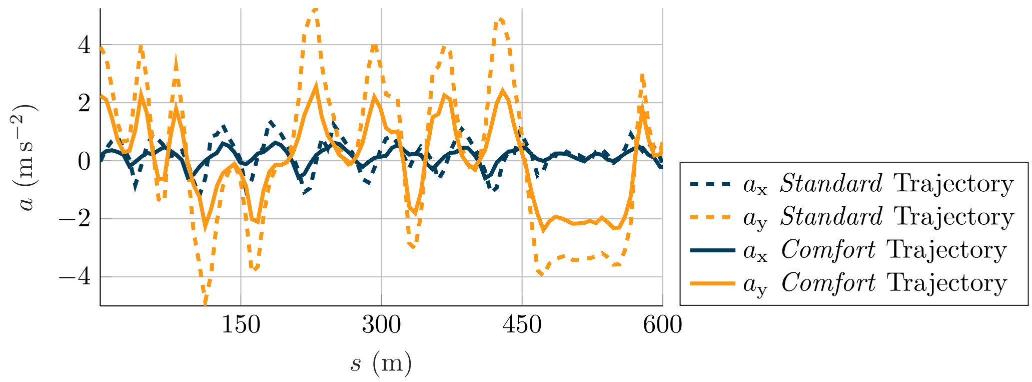

Figure 3: Longitudinal a_x and lateral a_y acceleration profiles of the reference trajectories.

The study is conducted using a *Hyundai IONIQ 5* that is equipped with a drive-by-wire system, which allows controlling the steering, throttle, and braking systems. A tracking controller [24] is utilized to ensure the vehicle tracks the reference trajectories repeatedly. The study is conducted with minimal changes in environmental influences, e.g., temperature and lighting. This ensures that the cause of motion sickness is consistent across all participants.

The Motion sickness susceptibility questionnaires (MSSQ) [25] is used prior to the study to assess the motion sickness susceptibility of the participants. It is a standardized tool designed to measure an individual's susceptibility to motion sickness. During the study, the MIsery SCale (MISC) [26] is employed to evaluate motion sickness symptoms. The MISC captures subjective symptoms of motion sickness on a scale from 0 to 10: 0 indicates *No Problems*, Nausea-related symptoms start at 6, and 10 indicates *Vomiting*. Each participant must rate their motion sickness symptoms using MISC every two minutes during the study. Participants have the option to stop the study at any time and are recommended to do so if their MISC rating reaches 6.

Participants of the study are seated on the right-hand side of the vehicle, both in the front and the rear seats. To ensure consistent visual perception of all participants, the participants need to solve Sudoku puzzles while driving. Each drive lasts for 30 min. Thus, participants repeatedly experience the *standard* or *comfort* trajectories for multiple laps.

A total of 18 participants drove the *standard* trajectory, with 9 of them in the front seat and 9 of them in the rear seat. Equivalently, 16 participants drove the *comfort* trajectory, with 8 of them in the front seat and 8 of them in the rear seat.

Note that unlike in manually driven studies [23], [27], our study is designed so that the variance in motion sickness ratings is as exclusively attributed to the individual motion sickness response as possible.

4 Results

The evaluation of the study shows that there is a significant difference between the participants' MISC ratings, even within the two groups of participants. This can be seen in Figure 4, which depicts the MISC self-rating of participants experiencing the *standard* trajectory.

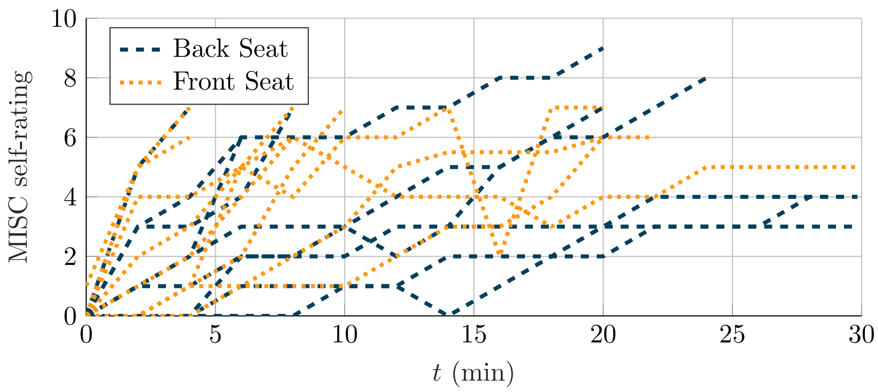

Figure 4: Participant MISC ratings experienced acceleration from the *standard* trajectory in both front and back seats.

At the end of the drives, either after 30 min or at an early stop, every participant experienced some symptoms of motion sickness, rated at least 3 on the MISC scale. Participants in the front seat reported slightly higher MISC ratings, with an average rating of 3.3 compared to 3.14 in the back seat. In addition, the average final rating of 6.44 of participants seated in the front seat is slightly higher than the average final rating of 6.11 of participants seated in the back seat. As the difference in the ratings between the front and the back seats is small, we neglect the seating position of the participants in the following.

To compare the MSDV to the MISC ratings in the study, we use the illness rating (IR) scale to describe the average motion sickness within a group. The authors in [16] report that the IR ratings: 0 - *All right*, 1 - *Slightly unwell*, 2 - *Quite ill*, and 3 - *Absolutely dreadful* are linearly related to the MSDV with the following conversion:

$$\mathrm{IR} = {}^{1}\!/\!_{50} \cdot \mathrm{MSDV}.$$

The MSDV model (1) uses the accelerations $a_i(t)$, $i = \{\mathrm{x}, \mathrm{y}, \mathrm{z}\}$. Analyzing the frequency-weighted, squared accelerations experienced by the participants reveals that $a^2_{\mathrm{y,w}}$ is substantially larger than $a^2_{\mathrm{x,w}}$ and $a^2_{\mathrm{z,w}}$. Particularly, $\int_0^{T(s)} (a_{\mathrm{y,w}}(t))^2 \, \mathrm{d}t = 525\,\mathrm{m}^2\,\mathrm{s}^{-4}$ significantly exceeds $\int_0^{T(s)} (a_{\mathrm{x,w}}(t))^2 \, \mathrm{d}t = 15\,\mathrm{m}^2\,\mathrm{s}^{-4}$ and $\int_0^{T(s)} (a_{\mathrm{z,w}}(t))^2 \, \mathrm{d}t = 0.20\,\mathrm{m}^2\,\mathrm{s}^{-4}$ at the end of one lap at $s = 614\,\mathrm{m}$, as depicted in Figure 5. This difference results from the lateral accelerations $a_{\mathrm{y}}(t)$ being larger than the longitudinal acceleration $a_{\mathrm{x}}(t)$ and vertical acceleration $a_{\mathrm{z}}(t)$, cf. Figure 3.

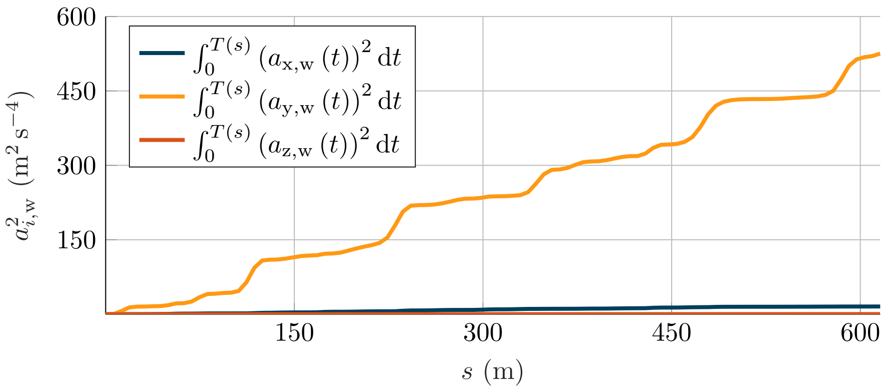

Figure 5: Weighted, squared accelerations for the longitudinal, lateral, and vertical directions accumulated over one lap of the *standard* trajectory.

According to [19], [28], the longitudinal and lateral acceleration have an equal influence on motion sickness perception. Similarly, in [23], all weighting factors of the MSDV model are set equally ($K_{\mathrm{x}} = K_{\mathrm{y}} = K_{\mathrm{z}}$). Because of the equal influence of all accelerations in the MSDV, the larger lateral acceleration results in a greater impact on the MSDV value. Given this, the longitudinal and vertical accelerations are neglected in the subsequent considerations. Therefore, the lateral acceleration is the only acceleration considered in the further application of the MSDV model to predict the IR:

$$\mathrm{IR} = \frac{1}{50}\sqrt{K_{\mathrm{y}} \int_0^T (a_{\mathrm{y,w}}(t))^2 \, \mathrm{d}t}. \tag{3}$$

We fit the MSDV model to the results of the study to evaluate the effectiveness of the lateral MSDV model in predicting motion sickness. Figure 6 depicts the MISC ratings of the *standard* trajectory as well as the MISC ratings for the *comfort* trajectory.

First, (3) is fitted to the MISC ratings of the *standard* trajectory using Non-Linear Least Squares (NLS) regression. To comply with the findings of [16], the fitting process is performed such that an IR of 3 corresponds to a MISC rating of 10.

The fitting yields $K_{\mathrm{y,s}} = 0.649$ and an Root Mean Square Error (RMSE) of 1.97 on the MISC scale. In comparison, the lateral acceleration weighting parameter ($K_{\mathrm{y,d}} = 0.55$) determined in [20] differs by approximately 15 % from the value identified in our study. Both predictions of the MSDV model that only uses the respective lateral acceleration weighting parameter are presented in Figure 6. The slight difference in the weighting parameter can be noted in the trajectory of the IR, in which the fit with $K_{\mathrm{y,s}}$ shows minor deviation from the prediction that uses $K_{\mathrm{y,d}}$ of the *standard* trajectory.

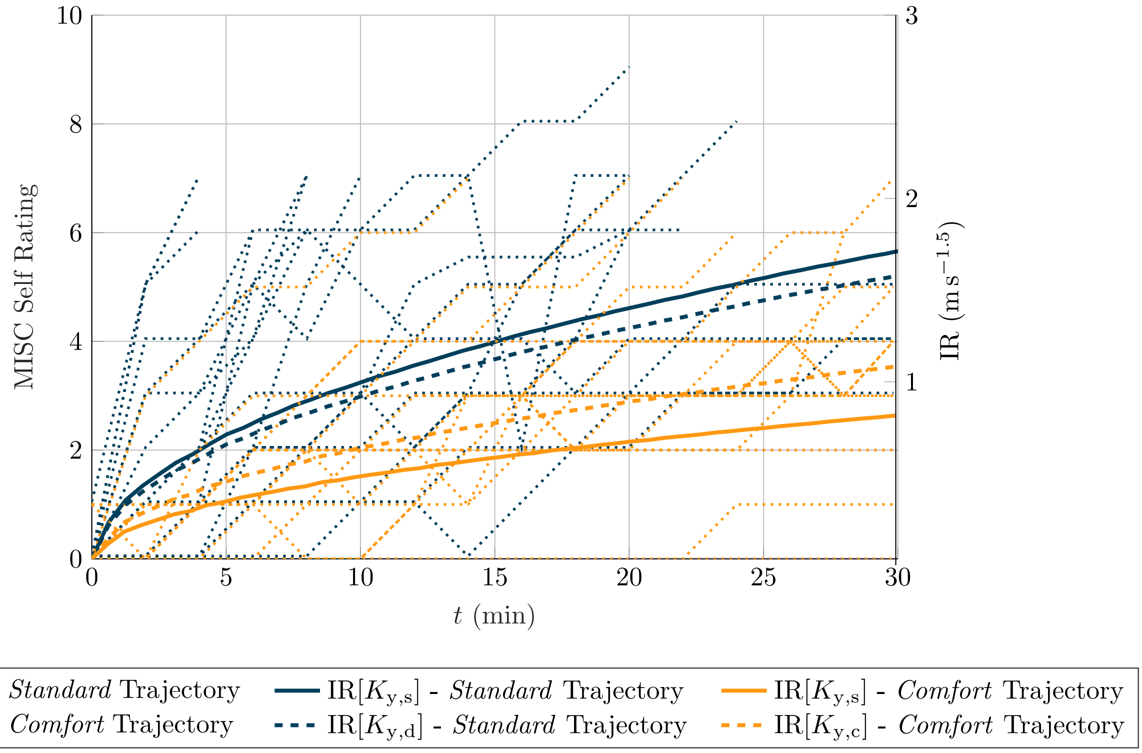

Figure 6: Participants MISC ratings compared to MSDV predictions with $K_{\mathrm{y,s}}$, $K_{\mathrm{y,d}}$, and $K_{\mathrm{y,c}}$ for drives with *standard* and *comfort* trajectories.

To demonstrate the scalability of the model to different inputs, we extrapolated the IR response using the previously identified parameter $K_{\mathrm{y,s}}$ and the acceleration data of the *comfort* trajectory. The MSDV model with $K_{\mathrm{y,s}}$ successfully predicts the MISC ratings of participants who experienced the *comfort* trajectory, resulting in an RMSE of 1.62 on the MISC scale. The reduction in RMSE compared to the fit for *standard* trajectory MISC ratings can be explained by the lower absolute values observed in the MISC ratings of the *comfort* trajectory.

To further evaluate the model's fit to reduced accelerations, we perform a second fitting of the lateral MSDV model to the MISC ratings of the *comfort* trajectory using NLS regression. The resulting value of $K_{\mathrm{y,c}}$ results in a RMSE of 1.49, which is smaller than the RMSE of the prediction. Both the prediction with $K_{\mathrm{y,s}}$ and the fit with $K_{\mathrm{y,c}}$ are depicted in Figure 6, which highlights the difference between the two. Note that the IR prediction of the *standard* trajectory using $K_{\mathrm{y,s}}$ (fitted to higher accelerations) performs only 8.7 % worse in terms of the RMSE compared to fitting the model directly to the MISC data of the *comfort* trajectory. Therefore, reducing the predicted IR by decreasing the lateral acceleration of the driven trajectory leads to a reduction of the MISC ratings.

Our results support the idea of incorporating the lateral MSDV model into motion planning algorithms to minimize the predicted lateral IR, and consequently to mitigate motion sickness symptoms for passengers in automated vehicles. This complies with current research showing that planning algorithms can generate trajectories that minimize the predicted IR [5], [21], [22].

5 Conclusion

This study validates that the lateral MSDV model is an effective tool for predicting motion sickness in automated driving scenarios. By fitting the model to experimental data, we derived a lateral acceleration weighting parameter $K_{\mathrm{y,s}}$ that closely aligns with established values presented in related literature. The MSDV model demonstrates scalability and accurately predicts motion sickness levels across different trajectories with varying acceleration profiles. Particularly, the MSDV model fitted to higher lateral accelerations (*standard* profile) performed well compared to a separate fit to lower accelerations (*comfort* profile). These findings highlight the potential of the MSDV model to be used in motion planning. Employing the MSDV model in motion planning has the potential to enable automated vehicles to minimize motion sickness through reduced lateral accelerations and, thus, to enhance passenger comfort and acceptance of autonomous driving technologies.

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