Optimal speed profile on a given road for motion sickness reduction

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Abstract

Motion Sickness (MS) is an issue of most transportation systems. Several countermeasures for such problem in cars are proposed in the literature, but most of them are qualitative, behavioural or involving complex chassis systems. With the growing interest in self-employed vehicles, the issue of MS may be so important that it undermines their benefits in terms of increased productivity; not addressing such issue may limit the users’ acceptance reducing the safety and environmental impact of autonomous vehicles. The present study presents a novel approach to combine minimal travel time with minimal Motion Sickness Incidence (MSI) by optimising the speed profile for a given path. Through simulation, a simple vehicle model is used to compare several strategies evaluating which of them are effective and which not. The optimisation task is formulated as a Non-linear Model Predictive Control (NMPC) and a series of optimisation routines are computed along the path; the strategies are implemented within the cost function of the NMPC problem evaluating their performance and if using a numerical MS model is mandatory to get a significant reduction of the MSI. The results show that not all the cost functions are effective, but it is possible to reduce MS without modelling its dynamics; however, the strategy taking into account the current MSI using a MS model outperforms the other cost functions in term of efficacy and efficiency. Such a quantitative approach can be used during motion planning in autonomous vehicles, to suggest an optimal speed in human-driven vehicles and to improve the comfort for bus-line services or even trains.

Keywords: Motion sickness, Nonlinear model predictive control, Vehicle comfort, Mission planning, Passenger modelling, Subjective vertical conflict theory

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1. Introduction

MS is a known issue in transportation systems since ancient times. The most famous versions of MS are sea-sickness, car-sickness, air-sickness and space-sickness; however, in recent times simulator-sickness and virtual reality-sickness are different versions of the same issue with a growing interest for the scientific community.

The main theory explaining MS is the conflict theory by Reason and Brand (1975): the acceleration perceived conflicts with the expected one generating a conflict leading to MS; this phenomenon is amplified when there is a conflict between the information coming from different sensorial paths: when a passenger in a car is reading it is more likely to be motion sick because of the visual information of the standing field of view conflicts with the vestibular system perceiving the actual acceleration of the vehicle, the reader should refer to Bronstein et al. (2020) for a more detailed description of the visual-vestibular conflict. Young (1978) shows that the visual-vestibular interaction is dominated by the visual information for frequencies below 0.1 Hz, while vestibular information dominates higher frequencies perception. As O’Hanlon and McCauley (1973) shows, the most critical acceleration frequencies for MS are the ones where there is no clear dominant path in the motion perception: the percentage of people that experienced emesis, called MSI, is maximum at \( \approx 0.17 \) Hz and is significant for frequencies from 0.01 Hz to 1 Hz.

The research interest is very strong because such frequencies are characteristic for all transportation systems, so every kind of transportation system is affected by different versions of the same issue: sea-sickness was the first as per Irwin (1881), nevertheless, further studies have continued in more recent years and lead to the fundamental experimental studies of O’Hanlon and McCauley (1973); Lawther and Griffin (1986); airsickness is also studied as per Turner et al. (2000); space sickness is another variant of the same issue in a slightly different context and an example of the scientific interest is in Oman (1987); trains are studied by Bertolini et al. (2017); Braccesi et al. (2013); road vehicles are widely studied as in Wada et al. (2010); Sugiura et al. (2019); Bronstein et al. (2020). Simulators are also widely studied because in such contexts the visual-vestibular conflict can be quite extreme due to vection; therefore several scientists as Kennedy et al. (1993); Ohyama et al. (2007); Zużewicz et al. (2011) studied such topics.

1.1. Autonomous driving: challenge or opportunity?

Autonomous driving is one of the most interesting growing technologies in the transportation field: it should bring safer roads avoiding human errors (Winkle (2016)) and should decrease the environmental impact of road transportation (Fagnant and Kockelman (2014)); the expected increase in passengers’ productivity is instead debated within the scientific community (Singleton (2019)): one of the greatest issues in being productive in an automated vehicle is indeed MS (Diels et al. (2016)).
The proposed countermeasures for MS in vehicles are mostly qualitative: Diels and Bos (2016) suggest to maximise the visual field of the occupants and to avoid rearward orientation of seats; Wada et al. (2010) suggest to lean inward the head when approaching a turn to keep the head more aligned with the gravitoinertial acceleration; indication about future vehicle motion can be helpful as per Kuiper et al. (2020), however, implementing head-up displays showing the planned trajectory as per Feenstra et al. (2011), might be infeasible for multi-seated cars. A more quantitative approach has been proposed by Sugiuara et al. (2019) using tilting seats to be more consistent compared to the head tilting strategy; however, similar approaches in tilting trains gave unclear results as per Cohen et al. (2011); Bertolini et al. (2017).

The idea of the authors is to try to exploit the peculiarities of autonomous vehicles: given a path, is it possible to define an optimal speed profile to minimise MSI and travel time for that mission?

To evaluate such capabilities, a numerical model of MS is needed.

1.2. Numerical models for motion sickness: ISO approach and subjective vertical conflict theory

Numerical models for MS can be classified under two main categories: ISO-like approach and Bos&Bles-like ones. In Lawther and Griffin (1987) a method to estimate MS by filtering the acceleration is presented; the integral of the squared filtered acceleration should be proportional to the MSI; ISO, 2631–1:1997 standard is based on Lawther and Griffin model. In Bos and Bles (1998), a method is proposed modelling the mechanism of motion perception for vertical motion; three dimensional extensions of such modelling are proposed by Braccesi and Cianetti (2011); Kamiji et al. (2007). In Braccesi and Cianetti (2011) a comparison between their UniPG model and the ISO one is showing that the UniPG model fits more consistently the literature data; furthermore, the Bos&Bles derived models are capable of modelling the decrease in MSI when the stimulus stops, while the ISO model defines the MSI as a monotone positive value over time.

Despite these models are needed to assess the performance of the MS reduction strategy implemented in this paper, are they really necessary to get a reduction in MS?

1.3. Optimal approach to motion sickness reduction: a generalised quantitative approach

Now that the issue of MS has been introduced as well as some proposed countermeasures and numerical models, the goal of this research can be clearly defined: finding an optimal way to travel on a path trading off minimum travel time and minimal MS. Such technique, if proven to be effective, may be used to plan speed profile of an autonomous vehicle, to suggest an optimal speed profile to a human driver or to plan a more comfortable speed profile for bus line services or train services. Such a solution can be combined with the techniques available in the literature to further reduce MS; its main benefits compared to the one already available in the literature are:
• it does not rely on passenger behaviour,
• it can be applied to already designed vehicles,
• it does not require complex active systems on the vehicle
• it does not require complex Human-Machine Interface (HMI) in the vehicles

Using the numerical model to assess the performance of the proposed algorithm allows to quantitatively evaluate the results only on an average estimate of the population. In an actual implementation of this technique, such a limitation may be overcome by allowing the users to tune how strong the MS reduction part of the optimisation should be; using a multi-objective cost function like the ones presented in this article lead to a straightforward implementation of this tuning by varying the MS related cost in the cost function.

2. Methods

A simulation approach is used to compare different strategies to optimise speed profile on a given path. The results are analysed to understand if the modelling of MS dynamics is the best approach to the trade-off between minimum travel time and MS reduction or some strategy may be effective without explicit modelling of MS.

The problem is implemented as a series of NMPC problems representing the path through a series of sequential optimisations, leading to a formulation independent of path length. An ideal representation of the simulated model has been assumed in the NMPC problem, so the initial conditions of optimisation are imposed equal to states and input of the second step of the previous optimisation. The NMPC has been implemented in MATLAB and solved using the fmincon solver. As shown in O’Hanlon and McCauley (1973), MS frequencies range from 0.01 Hz to 1 Hz, therefore the simulation step size has to be set to at least 2 Hz to get a proper description of MS dynamics. To achieve such frequencies each optimisation space step size is defined as space travelled in 0.5 s at the optimisation initial velocity. This approach leads to a different step size between low-velocity sharp turns and high-speed straights preventing an inefficient low step size due to the space transformation.

A test path is represented using a two-dimensional spline: the road used in this paper is a 120 km part of an Italian motorway. The spline is created from an internet map service, transforming the latitude-longitudinal waypoints in North-East-Down coordinates leading to a flat x-y description of the test path. Several map services were compared, but different waypoints density between map services does not lead to significant changes in the resulting spline. Neglecting the vertical contribution of the road, no vertical motion is present simplifying the formulation to a two-dimensional problem. The path can be divided in two main sections: a first winding section characterised by a mountain crossing and a final straighter section; the first section is long nearly twice the
Table 1: Description analysed cost functions

| Name               | Description                                                                 |
|--------------------|-----------------------------------------------------------------------------|
| Minimum time       | Reference model that minimise travel time. Small cost on the input avoids excessive variation in the input. |
| Jerk cost          | Like minimum time, but with a high cost on the longitudinal jerk to reduce MS |
| Acceleration cost  | Minimum time plus a cost on the acceleration modulus to reduce MS            |
| MS cost            | Minimum time plus an MS cost using the instantaneous disturb of the UniPG model |
| Adaptive MS cost   | Similar to the previous one; the MS cost is multiplied with the MSI          |

later one. Since automated driving will first used in motorways, the authors chose to use this scenario for their simulations; however the proposed approach is not limited to this scenario.

To get the acceleration of a vehicle moving on the path a vehicle model is needed; since the focus is not about a specific type of vehicle, but the optimisation of the given path, the simplest vehicle model is adopted: a point-mass model, which is fast to compute while being general for different vehicles. Motion sickness is modelled using the Braccesi and Cianetti (2011) model; the UniPG model is computed for every strategy tested to get the evolution of the MS incidence along the path, even if not used in the cost function. To be more representative of a touring driving, the vehicle acceleration has been constrained to be less than 0.3 g. The jerk is also constrained to generate a smooth acceleration profile within $\pm 3 \text{m/s}^3$. The vehicle is constrained on the spline, without any displacement in the normal direction, therefore the input of the model is only the longitudinal jerk; the lateral acceleration is computed from the longitudinal velocity and the path curvature. To avoid issues due to the constant changing curvature during optimisation, the problem has been space transformed like in Gao et al. (2012), so it is space integrated instead of time-integrated. This allows for a fixed curvature during the optimisation, even if it leads to a non-linear vehicle model; since the MS model is non-linear in itself, non-linearity in the vehicle model was considered of minor concern and it was preferred to a changing curvature. A detailed description of the model equations is given in Certosini et al. (2019).

The analysed strategies trading-off between MS and travel time are implemented in several cost functions of the NPMC problem, their results are compared to understand which is the most effective in preventing MS while keeping minimal travel time. The cost functions analysed in this paper are described in table 1, the equations are shown in table 2, with the notation explained in table 3.

The analysed cost functions can be divided into model-free and model-based: the model-free approaches use some kinematic quantities like jerk and accelerat-

5
### Table 2: Cost functions equations

| Name              | Cost function                                                                 |
|-------------------|-------------------------------------------------------------------------------|
| Minimum time      | $C_t \frac{1}{v_t} + C_u j_t$                                                  |
| Jerk cost         | $C_t \frac{1}{v_t} + C_j j_t$                                                  |
| Acceleration cost | $C_t \frac{1}{v_t} + C_u j_t + C_a (a_t^2 + v_t^2 \ast \rho(s))$               |
| MS cost           | $C_t \frac{1}{v_t} + C_u j_t + C_{MS} h$                                      |
| Adaptive MS cost  | $C_t \frac{1}{v_t} + C_u j_t + C_{MS} h_{MSI}$                                |

### Table 3: Cost functions variables

| Symbol | Description                                                                 |
|--------|----------------------------------------------------------------------------|
| $C_t$  | Minimum time cost                                                          |
| $C_u$  | Small input (jerk) cost to reduce input constraints violation               |
| $C_j$  | Big input (jerk) cost to reduce MS                                          |
| $C_a$  | Acceleration cost                                                          |
| $C_{MS}$ | Motion sickness cost                               |
| $v_t$  | Tangential velocity                                                        |
| $j_t$  | Tangential jerk (input)                                                    |
| $a_t$  | Tangential acceleration                                                    |
| $\rho$ | Path curvature                                                             |
| $s$    | Space (independent variable)                                               |
| $h$    | MS instantaneous disturb (as in Braccesi and Cianetti (2011))              |
| $MSI$  | MSI (as in O’Hanlon and McCauley (1973) and computed as in Bos and Bles (1998)) |
tion to reduce MS, while the model-based ones use the UniPG model to reduce its incidence. The first model-free cost function uses the jerk because it is a quantity related to comfort, so it is interesting to understand if it may be useful for this purpose. The other one uses the acceleration: since the MS models use often the acceleration as their input, as in O’Hanlon and McCauley (1973); Lawther and Griffin (1987); Bos and Bles (1998); Braccesi and Cianetti (2011), it is interesting to understand if reducing the input without modelling its dynamics may be sufficient to reduce the incidence of the discomfort. A simple reduction of the maximum acceleration allowed without modifying the cost function has been proven in Certosini et al. (2019) to be ineffective. The model-based cost functions use the UniPG model to compute the instantaneous disturb variable $h$ and the current motion sickness incidence variable $MSI$ due to the evolution of the disturb: those are described in Braccesi and Cianetti (2011) respectively as a sort of non-linear-weighted filtering of the accelerations and as a sort of second-order leaking-integrator; for a detailed description of their mathematical formulation as block diagrams check Bos and Bles (1998); Braccesi and Cianetti (2011), while their formulation in terms of state equations is shown in Certosini et al. (2019). The simple one has a cost $C_{MS}$ on the instantaneous disturb $h$: since $h$ is the most direct source of $MSI$, applying a cost on $h$ may be the most straightforward approach to reduce MS; the drawback of such approach is that the weight in the cost function does not take in account the $MSI$, so even in a path too short to have a significant incidence the vehicle is slower than using the baseline cost function without significant advantage in terms of comfort. A more advanced approach is to use both the instantaneous disturb and the incidence: the instantaneous disturb is weighted both by its cost $C_{MS}$ and $MSI$. This approach, compared to the previous one, is capable of adapting itself to the road characteristics: if the road is too short to be relevant for MS, a low $MSI$ will allow to a speed profile close to the minimum time one, when the path is long it will slow-down the vehicle during winding sections; due to this characteristic, the more advanced model has been named adaptive MS model.

The performance of each cost function is assessed using the UniPG model comparing the maximum $MSI$ obtained along the path against the travel time; the lower the time with the same maximum $MSI$, the more efficient the cost function is. The results are also evaluated using the ISO, 2631–1:1997 model: coherent results would confirm their robustness to the metric used; to do that the fifth-order filter proposed in Zuo and Nayfeh (2003) is used to approximate the ISO filter.

3. Results

The results are summarised in figure 1: the shorter the travel time and the lower the $MSI$ the better; for a list of cost values for the various runs see table 4.

The base model is, obviously the fastest, with a travel time of $\approx 58$ min; the maximum $MSI$ of $\approx 32\%$ indicates quite a severe risk of emesis.
Cost functions comparison

Figure 1: Maximum MSI over total travel time for the analysed cost functions

Table 4: Simulation results

| Cost function       | Cost  | MSI max (%) | Travel Time (min) |
|---------------------|-------|-------------|-------------------|
| Minimum time        |       | 31.7        | 58 min 26 s       |
| Jerk cost $C_j = 40$|       | 43.7        | 1 h 7 min 31 s    |
| Jerk cost $C_j = 200$|      | 41.3        | 1 h 6 min 43 s    |
| Jerk cost $C_j = 1500$|     | 38.6        | 1 h 7 min 55 s    |
| Acceleration cost   | $C_a = 10$ | 21.3        | 1 h 11 min 0 s    |
| Acceleration cost   | $C_a = 15$ | 19.8        | 1 h 14 min 42 s   |
| MS cost $C_{MS} = 75$|      | 23.1        | 1 h 9 min 22 s    |
| MS cost $C_{MS} = 140$|     | 21.0        | 1 h 11 min 32 s   |
| MS cost $C_{MS} = 170$|     | 21.5        | 1 h 11 min 49 s   |
| MS cost $C_{MS} = 200$|     | 22.2        | 1 h 11 min 44 s   |
| Adaptive MS cost    | $C_{MS} = 24$ | 20.6        | 1 h 9 min 3 s     |
| Adaptive MS cost    | $C_{MS} = 25$ | 20.0        | 1 h 9 min 48 s    |
| Adaptive MS cost    | $C_{MS} = 27$ | 18.3        | 1 h 11 min 37 s   |
| Adaptive MS cost    | $C_{MS} = 30$ | 17.7        | 1 h 12 min 9 s    |
| Adaptive MS cost    | $C_{MS} = 40$ | 14.8        | 1 h 16 min 20 s   |
Despite its usage for comfort assessment, using the jerk to reduce MS is ineffective. The jerk cost function has the highest MSI and it is also quite slow.

The acceleration cost function proves to be very effective: it provides a significant reduction of MSI over the minimum time strategy and varying $C_a$ affects the trade-off between minimum time and low MSI.

An interesting result is the simple MS cost function one: just optimising $h$ in the optimisation is effective indeed, but it is not more effective than just trying to reduce the acceleration. For the same MSI peak value, the travel time is usually higher than the acceleration run, therefore such technique is less efficient than the acceleration strategy. For values of $C_{MS}$ in the $140 - 170 - 200$ range, the model has almost the same MSI and the same travel time, possibly due to some numerical issues for this cost function.

The adaptive MS cost function is the best performer of all those tested. This cost function provides the lowest MSI among all and is substantially the most efficient between the three effective ones in reducing the MSI: comparing the runs with $C_a = 10$, $C_{MS} = 140$ and $C_{MS} = 24$, the adaptive cost functions is faster by over two minutes compared to the others. When looking for lower MSI values, the difference in time between the adaptive cost function and the acceleration cost function increases dramatically: lowering the maximum MS from 21% to 20% the difference in time rise from $\approx 2$ min to $\approx 5$ min.

When looking at a travel time of $\approx 71$ min, the adaptive cost function reduces the maximum MSI to $\approx 18\%$ instead of the $\approx 21\%$ of the acceleration and simple MS cost functions.

Looking at the evolution of the MSI over time for runs with similar maximum
MSI (figure 2), the difference between the adaptive cost function and the simpler MS one is interesting: at the beginning, the lower overall MS cost ($C_{MS\text{ MSI}}$) give higher MSI values, however, for higher MSI, the adaptation of the more complex cost function gives its benefits keeping the MSI below the simpler cost function.

When comparing runs of similar duration (figure 3), it is clear how the adaptive cost function outperforms the others.

4. Discussion

The results show that the presented optimisation is effective in reducing passengers discomfort. Introducing additional terms within the motion planning algorithm to increase passengers comfort is effective even without actively modelling the MS dynamics as for the acceleration cost function. The best strategy for a simple implementation of an MS reduction algorithm might be the acceleration cost, but, for the best performance in terms of MS reduction and minimal time, an adaptive MS strategy is needed; the simple MS strategy is not more effective than the acceleration cost not justifying the additional burden of optimising the MS dynamics. The MSI data can be used as a feedback to the passengers: when using the acceleration cost, the MSI needs to be computed as a separate task from the optimisation, while using an adaptive MS strategy, the information is already available.

It is interesting to notice how the acceleration cost function is effective while a further reduction of the maximum acceleration is not, as shown in
Given the innate variability from person to person in the phenomenon of MS, the numerical models are not so accurate; so it is interesting to compare the obtained results between the proposed cost functions using the ISO 2631:1997 approach to understand if the results are consistent and can be taken as a general improvement of comfort. The results showed in figure 4 are consistent with the ones in figure 3: the adaptive cost function is the most effective approach and the most efficient and the simple MS and acceleration cost functions have similar performance; it is interesting to notice the adaptation phase in the first minutes of the adaptive cost function. Such coherency suggests that the proposed strategies do indeed offer an improvement in terms of MSI and that this improvement is not just a numerical trick due to the use of the same algorithm in optimisation and performance evaluation.

Despite leading to similar results, is shown in Braccesi and Cianetti (2011) that the UniPG model fits much better the experimental results of O’Hanlon and McCauley (1973); Golding et al. (1997) compared to ISO, 2631–1:1997; according to this, results in figure 1 are to be considered more reliable.

The usage of a Bos&Bles-derived model for the computation of the MSI to be used in the cost function is key to model the decrease in MSI in straight stretches that follow winding sections, which is important in the adaptive cost function. Using ISO-like modelling would have led to an indefinitely increasing MSI over time, resulting in an unjustified slowing down of the vehicle on any straight stretch that follows tortuous sections, while it is a common experience that without or with small enough stimuli the sickness will eventually decrease.
The results of this research show that it is possible to improve passengers comfort and to reduce MSI by taking into account comfort-related terms in the optimisation during mission planning; it is shown how modelling their physiological dynamics is not mandatory to reduce MSI, but using a numerical model with the proposed adaptive cost function is essential to have good performance and efficiency.

The adaptive approach for mission speed profile optimisation is the main contribution of this paper, allowing for fine-tuning with small variations of the motion-sickness-related cost and the best performance in terms of both incidence reduction and minimal travel time. The systematic comparison of the possible cost functions to reduce the MSI while minimising travel time is another contribution demonstrating that it is possible to obtain a reduction of the MSI without modelling its dynamics.

5. Conclusion

The presented study introduces a new approach to optimise speed profile on a given path: reducing MSI while still minimising travel time can significantly improve the acceptance of automated driving technologies. The same approach can be used to improve comfort for human-driven cars advising the driver with the best speed or to improve services like intercity buses ones or even trains implementing MS estimations while planning travel times; the approach proposed is not limited to autonomous vehicles given the simple vehicle model.

The proposed techniques can be integrated into motion planning algorithms for autonomous driving control to extend their benefits when the path definition is computed in real-time and not a priori defined like in this article.

To give the possibility to the users to interactively fine-tune the trade-off between MS and travel time minimisation like in an adaptive cost function may greatly improve users’ acceptance for autonomous vehicles and therefore improving their adoption, with the resulting benefits in terms of safety and environmental impact of transportation.

References

Bertolini, G., Durmaz, M.A., Ferrari, K., Küffer, A., Lambert, C., Straußmann, D., 2017. Determinants of Motion Sickness in Tilting Trains: Coriolis/Cross-Coupling Stimuli and Tilt Delay. Frontiers in Neurology 8, 195. doi:10/ggqc6r.

Bos, J., Bles, W., 1998. Modelling motion sickness and subjective vertical mismatch detailed for vertical motions. Brain Research Bulletin 47, 537–542. doi:10/b9spaq.

Braccesi, C., Cianetti, F., 2011. Motion sickness. Part I: Development of a model for predicting motion sickness incidence. International Journal of Human Factors Modelling and Simulation 2, 163. doi:10/fx2m69.
Braccesi, C., Cianetti, F., Scaletta, R., 2013. Development of a Methodology for the Evaluation of Motion Sickness Incidence in Railways, ASME. p. V013T14A045. doi:10/ggqc6s.

Bronstein, A., Golding, J., Gresty, M., 2020. Visual Vertigo, Motion Sickness, and Disorientation in Vehicles. Seminars in Neurology 40, 116–129. doi:10/ggqc6w.

Certosini, C., Papini, L., Capitani, R., Annicchiarico, C., 2019. Preliminary study for motion sickness reduction in autonomous vehicles: An MPC approach. Procedia Structural Integrity 24, 127–136. doi:10/ggqc6v.

Cohen, B., Dai, M., Ogorodnikov, D., Lauren, J., Raphan, T., Müller, P., Athanasios, A., Edmaier, J., Grossenbacher, T., Stadtmüller, K., Brugger, U., Hauser, G., Straumann, D., 2011. Motion sickness on tilting trains. The FASEB Journal 25, 3765–3774. doi:10/d38dcm.

Diels, C., Bos, J.E., 2016. Self-driving carsickness. Applied Ergonomics 53, 374–382. doi:10/gf4sn5.

Diels, C., Bos, J.E., Hottelart, K., Reilhac, P., 2016. Motion Sickness in Automated Vehicles: The Elephant in the Room, in: Meyer, G., Beiker, S. (Eds.), Road Vehicle Automation 3. Springer International Publishing, Cham, pp. 121–129. doi:10/dqsg.

Fagnant, D.J., Kockelman, K.M., 2014. The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. Transportation Research Part C: Emerging Technologies 40, 1–13. doi:10/f5wzd.

Feenstra, P., Bos, J., van Gent, R., 2011. A visual display enhancing comfort by counteracting airsickness. Displays 32, 194–200. doi:10/fnp6k9.

Gao, Y., Gray, A., Frasch, J.V., Lin, T., Tseng, E., Hedrick, J.K., Borrelli, F., 2012. Spatial Predictive Control for Agile Semi-Autonomous Ground Vehicles, in: Proceedings of the 11th International Symposium on Advanced Vehicle Control.

Golding, J.F., Phil, D., Finch, M.I., Stott, J.R.R., 1997. Frequency effect of 0.35-1.0Hz horizontal translational oscillation on motion sickness and the somatogravic illusion. Aviation, Space, and Environmental Medicine 68, 396–402.

Irwin, J., 1881. The pathology of sea-sickness. The Lancet 118, 907–909. doi:10/fnb6xz.

ISO, 1997. Mechanical Vibration and Shock — Evaluation of Human Exposure to Whole-Body Vibration — Part 1: General Requirements. ISO Standard 2631-1. International Organization for Standardization. Geneva.
Kamiji, N., Kurata, Y., Wada, T., Doi, S., 2007. Modeling and validation of carsickness mechanism, in: SICE Annual Conference 2007, IEEE, Takamatsu, Japan. pp. 1138–1143. doi:10/fmvp69.

Kennedy, R.S., Lane, N.E., Berbaum, K.S., Lilienthal, M.G., 1993. Simulator Sickness Questionnaire: An Enhanced Method for Quantifying Simulator Sickness. The International Journal of Aviation Psychology 3, 203–220. doi:10/bbh54v.

Kuiper, O.X., Bos, J.E., Diels, C., Schmidt, E.A., 2020. Knowing what’s coming: Anticipatory audio cues can mitigate motion sickness. Applied Ergonomics 85, 103068. doi:10/ggp88p.

Lawther, A., Griffin, M.J., 1986. The motion of a ship at sea and the consequent motion sickness amongst passengers. Ergonomics 29, 535–552. doi:10/fk9tsh.

Lawther, A., Griffin, M.J., 1987. Prediction of the incidence of motion sickness from the magnitude, frequency, and duration of vertical oscillation. The Journal of the Acoustical Society of America 82, 957–966. doi:10/cw29cs.

O’Hanlon, J.F., McCauley, M.E., 1973. Motion Sickness Incidence as a Function of the Frequency and Acceleration of Vertical Sinusoidal Motion. Technical Report AD0768215. Office of Naval Research.

Ohyama, S., Nishiike, S., Watanabe, H., Matsuoka, K., Akizuki, H., Takeda, N., Harada, T., 2007. Autonomic responses during motion sickness induced by virtual reality. Auris Nasus Larynx 34, 303–306. doi:10/bbgrjr.

Oman, C.M., 1987. Spacelab experiments on space motion sickness. Acta Astronautica 15, 55–66. doi:10/chs3mb.

Reason, J.T., Brand, J.J., 1975. Motion Sickness. Academic Press, London, New York.

Singleton, P.A., 2019. Discussing the “positive utilities” of autonomous vehicles: Will travellers really use their time productively? Transport Reviews 39, 50–65. doi:10/ggp9z2.

Sugiura, T., Wada, T., Nagata, T., Sakai, K., Sato, Y., 2019. Analysing Effect of Vehicle Lean Using Cybernetic Model of Motion Sickness. IFAC-PapersOnLine 52, 311–316. doi:10/ggp88q.

Turner, M., Griffin, M.J., Holland, I., 2000. Airsickness and aircraft motion during short-haul flights. Aviation, Space, and Environmental Medicine 71, 1181–1189.

Wada, T., Fujisawa, S., Imaizumi, K., Kamiji, N., Doi, S., 2010. Effect of Driver’s Head Tilt Strategy on Motion Sickness Incidence. IFAC Proceedings Volumes 43, 192–197. doi:10/dkfpqf.
Winkle, T., 2016. Safety Benefits of Automated Vehicles: Extended Findings from Accident Research for Development, Validation and Testing, in: Maurer, M., Gerdes, J.C., Lenz, B., Winner, H. (Eds.), Autonomous Driving. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 335–364. doi:10/dqsh.

Young, L.R., 1978. Visually induced motion in flight simulation, in: AGARD Symposium on Flight Simulation, Brussels.

Zuo, L., Nayfeh, S., 2003. Low order continuous-time filters for approximation of the ISO 2631-1 human vibration sensitivity weightings. Journal of Sound and Vibration 265, 459–465. doi:10/dgpmtz.

Zużewicz, K., Saulewicz, A., Konarska, M., Kaczorowski, Z., 2011. Heart rate variability and motion sickness during forklift simulator driving. International journal of occupational safety and ergonomics: JOSE 17, 403–410. doi:10/ggqc6t.