Chapter XX

Analysis of Human Perception Models for Motion Sickness in Autonomous Driving

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ABSTRACT

Autonomous vehicle technologies are rapidly growing and are expected to change transportation habits radically. Autonomous cars increase the likelihood of motion sickness by allowing everyone in the vehicle to become passengers and perform non-driving tasks such as reading, working, and socializing. Comfort is one of the critical factors in the acceptance of autonomous vehicles. This makes accurate estimation of motion sickness a necessity in the development stages of autonomous vehicles. The sensory conflict theory is a widely accepted theory that explains the mechanism of motion sickness. Computational models based on the sensory conflict theory are used to predict motion sickness and contain two main parts: a human perception model and a nonlinear fitting function to the subjective feeling of motion sickness. Models of the human perception, including the dynamics of the vestibular system, are used to calculate the difference between sensory inputs and the predicted motions in the brain, i.e. the conflict signal, which is the primary cause of motion sickness. One of the main limitations of motion sickness prediction is how to mathematically model human perception because of the complexity of the psychophysiological systems. The aim of this work is to implement and analyse different human perception modelling techniques, such as observer framework in the control theory and optimal estimator approach using Kalman filters, to evaluate their abilities to integrate with motion sickness prediction. In this study, the different human perception models are implemented and analysed using MATLAB / Simulink and the advantages, as well as disadvantages of the models, are discussed.

Keywords: Human perception models, motion sickness, autonomous driving

INTRODUCTION

Motion sickness is one of the critical factors related to comfort that could be affecting the acceptance of autonomous driving. Vehicles driving in autonomous mode will allow the passengers to do Non-Driving Tasks (NDT), such as reading, socializing, etc., which can increase the chance of becoming motion sick (Sivak and Schoettle, 2015). The vestibular system plays a primary role in motion sickness, as given by the fact that people who do not have functioning vestibular organs do not become motion sick. There is a strong belief that motion sickness during travelling is caused by conflicting sensory information about the human state of motion. The vestibular system is a sensory system that is responsible for providing the brain with information about motion, head position, and spatial orientation. Therefore, a clear understanding of the dynamic behaviour of the vestibular system and human perception is crucial for analysing discomfort. The aim of this study is to analyse human perception estimation algorithms for identifying motion sickness in Autonomous Driving (AD). Provided analyses include computer simulations (in Matlab/Simulink) that can also be used for a better understanding of the model behaviour and human perception which further help to model motion sickness.

The block diagram in Figure 1 represents a general structure of the motion sickness models based on the sensory conflict theory, which consists of two main parts. The first part consists of mathematical models of the spatial orientation perception of humans, including the dynamics of the vestibular system. The vestibular organs consist of semicircular canals, which detect angular motions, and otoliths, which detect gravito-inertial force (GIF), and their dynamics are simply modelled as transfer functions. The second part of the sensory conflict theory-based model focus on modelling the subjective feeling of motion sickness using a conflict signal that comes from the human perception. The difference between the calculated signal by the neural system and sensed signal causes the conflict signal. The conflict signal is used as an input to a nonlinear function that accounts for the subjective feeling of motion sickness.

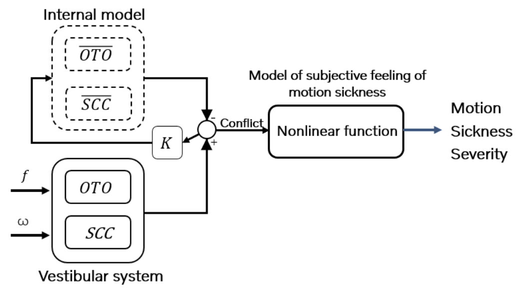


Figure 1. Sensory conflict theory-based motion sickness models

HUMAN PERCEPTION MODELING

For decades, researchers have configured models by conducting experiments and examining the responses of subjects to find an appropriate and reliable model of human perception. Merfeld developed a model in Luenberger (e.g. linear) observer framework (Merfeld and Zupan, 2002) which is one of the common methods for human perception modelling and builds on his previous work on squirrel monkeys (Merfeld, 1995). Haslwanter modified the Merfeld model to fit with the eye movement response during Off-Vertical Axis Rotation (OVAR) experimental tests done on human test subjects (Haslwanter et al., 2000). The observer approach has the advantage of merging multiple internal models into one observer to monitor different states and enable interaction between them. However, the gains are free parameters, so the modeler fine-tunes them to align with empirical observations. Furthermore, the estimates of the states are carried out without considering noise. However, the human sensory system is noisy and inaccurate; therefore, it is crucial to account for noise or uncertainty during state estimation.

The estimator approach to model human perception was pioneered by work by Borah et al. where they modelled the human perception using the Kalman filter estimator (Borah et al., 1979). The estimator is essentially representing the internal model that processes the error between the afferent response and the estimated sensory signal and replaces the static gain in the Luenberger observer models, with the Kalman gain which takes into account the fact that the measurement of the sensory dynamic and its process is noisy and non-deterministic. Further development was done by Pommellet by building an Extended Kalman Filter (EKF) model (Pommellet, 1990). The main difference to the Borah Kalman Filter is the use of quaternion integration to model the rotational velocity cue to relative gravity orientation, the use of visual saturation to take into account the vection phenomena, as well as the noise dynamics which are significantly different from the Borah model. Selva (Selva, 2009) proposed an Unscented Kalman Filter (UKF) based model which further developed the Pommellet EKF model. The improvement is based on that the accuracy of the EKF model is limited mathematically into first-order in terms of the posterior distribution states. Merfeld and Karmali implemented a Particle filter estimator since the statistical accuracy level observed in Kalman Filter, EKF and UKF are limited due to the Gaussian distribution assumption made in these methods (Karmali and Merfeld, 2012). The Particle Filter approach could lead to relatively high computational cost, but on the other hand it also uses a distributed and parallel processing of the processing dynamics which represent more realistic computational processing in the brain. An overview of human perception models in literature can be seen in Table 1.

Table 1: Overview of human perception models in the literature

Modelling Framework	Authors
Luenberger Observer	Haslwanter et. al. (2000), Merfeld (1995, 2002), Vingerhoets et. al. (2007), Newman (2009)
Kalman Filter	Borah (1979) and Lim et. al. (2017)
Extended Kalman Filter (EKF)	Pommellet (1990)
Unscented Kalman Filter (UKF)	Selva (2009)
Particle Filter	Karmali and Merfeld (2012)

Vestibular Organ Modeling

There is a common consensus in the research community that the *Otolith* could be modelled as an overdamped mass-spring-damper system based on the hair cell deflection of the organ which influences the afferent response to the CNS. The latest development has been done by Telban and Cardullo (Telban and Cardullo, 2005) and this is the most complete representation of the transfer function according to a literature review of various otolith models done by Asadi (Asadi et al., 2016). In observer-based human perception models, commonly a unity matrix is used to model the otolith organ dynamics. In the optimal estimator-based human perception models (e.g. Selva), the transfer function by Telban and Cardullo (Telban and Cardullo, 2005) is used. This transfer function is mathematically represented as

$$T_{OTO} = \frac{AFR(s)}{f(s)} = K_{OTO}\frac{(\tau_l s + 1)}{(\tau_L s + 1)(\tau_S s + 1)} = 33.3\frac{(10s + 1)}{(5s + 1)(0.016s + 1)}$$

where τ_a is the adaptation operator, τ_L is the lead time constant, τ_l is the longtime constant and τ_s is the short time constant, K_{OTO} is the static Otolith gain, AFR is the Afferent Firing Rate and f is the gravito-inertial force (GIF).

The other part of the vestibular organ modelling is the *Semicircular Canal.* It is commonly modelled using a torsion pendulum with a high degree of damping and specific parameters. The angular velocity vector is represented by ω_s and $\widehat{\omega}_s$ is the sensed angular velocity vector estimated by the internal model of semicircular canals. In observer-based human perception models, the semicircular canal organ is modelled with a 2nd order transfer function developed by Fernandez and Goldberg (Fernandez and Goldberg, 1971), (Telban and Cardullo, 2005) and (Asadi et al., 2017).

$$T_{SCC} = \frac{AFR(s)}{\omega_s} = \frac{\tau_l \tau_a s^2}{(\tau_a s + 1)\,(\tau_l s + 1)} = \frac{5.73 \cdot 80\; s^2}{(80s + 1)(5.73s + 1)}$$

where τ_a is the adaptation operator and τ_l is the long time constant. Haslwanter used the same transfer function with selected τ_a=7 and τ_l=190 (Haslwanter et al., 2000).

Motion Sickness Modeling

A widely recognised theory proposes that motion sickness is caused by a signal mismatch between the internal model in the brain and received signals from sensory organs. The sensory conflict theory-based models are focused on the mechanism of motion sickness and use a modelled vestibular system and Central Neural System (CNS). Current motion sickness models are based on the observer framework of control theory approaches of modelling human motion perception. The neural mismatch model was proposed by Reason (Reason, 1978) and after modelled mathematically by Oman (Oman, 1990). Bos and Bles proposed the Subjective Vertical Conflict (SVC) theory model called 1D-SVC, which interprets Oman's heuristic model (Bos and Bles, 1998 and 2002). Bos and Bles proposed a nonlinear fitting function to experimental results of subjective human motion sickness feeling due to vertical motion disturbances by McCauley (McCauley, 1976). Braccesi and Cianetti proposed an extended version of the 1D-SVC model to a 3D-SVC model called vestibular 3D model (UNIPG) and visual-vestibular models (UNIPGSeMo) (Braccesi et al, 2011a+b). A 6-DOF motion sickness model was proposed by Wada et al. (Wada et al., 2015) and Kamiji et al. (Kamiji et al., 2007). The Wada model expands the previously 1-DOF Bos and Bles model into a 6-DOF model by considering the interaction between the semicircular canals and the otolith organ. In this model, the nonlinear fitting method, feedback conflict mechanism, sensory dynamics, and internal model directly adapt from the Bos and Bles model. Moreover, the model also includes the rotational velocity cues contribution on the relative gravity representation from the Merfeld model. Recently, the 6-DOF mathematical model of motion sickness severity prediction has been extended by considering visual inputs (Wada et al., 2020). The main difference between the model by Wada and the previous human perception model by Merfeld is that the efference copy of body dynamic is modelled as a feedforward static gain. The static gain is then developed later into a dynamic feedforward gain (Wada, 2021) based on the sequential learning of the body dynamics by utilizing the Recursive Gaussian Process Regression (RGPR) method.

Evaluation and Test Methods

Two physiological parameters are considered in this study to determine the relationship between the human perception models and motion sickness models: The velocity storage time constant (τ_{VS}) and the subjective vertical time constant (τ_{SV}).

The velocity storage mechanism was firstly introduced by Raphan et al. (Raphan et al., 1979) as a mechanism that when the sensed perception afferents from cupula were passed to the CNS, they were processed with filters which have a certain time delay constant of a leaky integrator due to the neural storage, hence giving the prolonged rotational velocity sensation. The velocity storage time constant could be observed by calculating the time that it takes for the rotational velocity perception to decay to 36.8% of the peak value during trapezoidal input stimulus which is done in the Earth Vertical Axis Rotation (EVAR) tests.

The subjective vertical time constant could be observed by calculating the time it takes to reach the magnitude of 63.2% of the steady-state final condition during the Fixed Radius Centrifugation (FRC) test.

In this study, the human perception models and motion sickness models are assessed by their ability to predict these two parameters (τ_{SV} and τ_{VS}) in comparison with the experimental test results.

The EVAR validation for velocity storage time (τ_{VS}) was simulated by inputting the stimulus input of a trapezoidal yaw motion with the peak of 60 deg/s reached in a second (60 deg/s^2 rotational acceleration) during the acceleration and then keeping a constant peak value for 45 seconds. After that, the human was decelerated at the same rate as the acceleration. The simulation results are then compared with experimentally measured velocity storage time constant in yaw direction for adults (e.g. the average 17.4 s for normal subjects using eye movements recordings), according to Bertolini et al. (Bertolini et al., 2012).

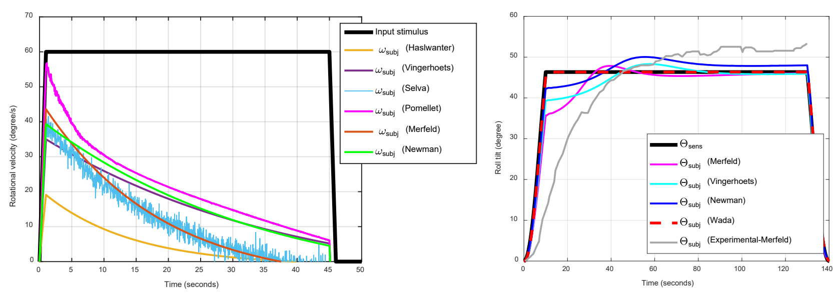
The subjective vertical time constant (τ_{SV}) in the Fixed Radius Centrifugation (FRC) test was experimentally performed by Merfeld (Merfeld, 2001). The FRC test comprises seated human subjects rotated in a simulator with a peak yaw velocity of 250 degree/s after 10 s of stimulation. Due to the centripetal force experienced at a radius of 0.54 m from the center of the rotation, the human subject will experience lateral acceleration as well with $a_y = -\omega^2 r$. The consequence of this experimental stimulation is that the direction between the perception of the GIF wrt. gravity compared against the direction of the sensed GIF wrt gravity, will be delayed with a certain time constant before the GIF perception goes past the steady-state sensed GIF and eventually reaches a steady-state condition as well. This time constant is called the subjective vertical time constant (τ_{SV}) and is calculated experimentally as an average of 28.1 s according to a study by Merfeld for the facing the motion setup while the humans were rotated in the clockwise direction (Merfeld, 2001). Special laboratory equipment was used to record the perceptual GIF tilt from subjects' perceived earth horizontal axis.

RESULTS AND DISCUSSION

From the simulation results presented in Figure 2 (a), it can be observed that the velocity storage time constant for the Merfeld (τ_{VS} = 17 s), Haslwanter (τ_{VS} = 13.4 s) and Selva (τ_{VS} = 16.7 s) models are in good agreement with the experimental velocity storage time constant of 17.4 s. The Pommellet model has given a velocity storage time constant (τ_{VS} = 20.8 s) which is higher with respect to the experimental results due to noise tuning (selected process noise Q = 0.3) in the model parameters. In addition, the Vingerhoets (τ_{VS} = 27.1 s) and the Newman model have overestimated the velocity-time constant (τ_{VS} = 26.1 s), due to the adaptation of the free gain parameters. However, Pommellet, Vingerhoets and Newman's models are still in the range of experimentally determined adult human responses.

For the subjective vertical time constant evaluation, it can be seen in Figure 2 (b) that Merfeld and Newman's models give the closest resemblance to the experimental result of average 28.1 s. The transient response of the Vingerhoets model behaviour is similar to Newman's model with a longer time delay to sense GIF tilt. The simulation results also show that the Wada motion sickness model could not predict the tilt angle perception (subjective vertical constant) as observed in the experimental tests but agreed with the physical stimulus which was also demonstrated by (Uefune et al., 2016). The results indicate that the human perception models which fit with the experimental results of human perception tests could be integrated with motion sickness models to improve their capability of motion sickness prediction. Irmak et al. (Irmak et al., 2021) have experimentally investigated the relationship of motion perception parameters (e.g. velocity storage and subjective vertical time constants) to motion sickness.

The Selva model which represents the estimator model with the biological noise in the measurement and process of the model is possibly the most plausible modelling source for further improvement of the available motion sickness models (e.g. Wada or UniPG), assuming that the noise are Gaussian distributed. Alternatively, the Particle filter approach by Karmali and Merfeld could also be used in the case that the sensory dynamics noise are of non-Gaussian distributed type.



(a) (b)

Figure 2. Simulation results for human perception and motion sickness models where θ_{sens} denotes sensed GIF tilt, θ_{subj} denotes subjective GIF tilt perception, ω_{subj} denotes the subjective rotational velocity perception. (a): velocity storage time constant evaluation under EVAR test. (b): the subjective vertical time constant evaluation under FRC test.

CONCLUSIONS

The main contribution of this paper is that different human perception models were implemented and evaluated under test conditions. The simulation results show that the implemented human perception models are able to predict the human adult range of sensation measured by experimental tests. These human perception models can also be tuned to fit with different experimental results of human perception. The study also indicates that accurate human perception modelling could improve the prediction of conflict signal estimation. Integrating accurate human perception models in motion sickness models can improve their capability to predict motion sickness feelings. For future studies, there is still a need to further investigate the integration of human perception models, which includes visual and somatosensory input, as well as improve the nonlinear function part that predicts the feeling of motion sickness.

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