Perception-based motion cueing: validation in driving simulation

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Abstract *– This paper describes a perception-based motion cueing (PBMC) algorithm, which aims to bridge the gap between what is known about human self-motion perception and what is currently used in motion simulation. In PBMC, motion perception knowledge is explicitly incorporated by means of a perception model and a cost function. PBMC has the potential of improving the realism of the motion simulation by exploiting the limitations and ambiguities of human self-motion perception and increasing the utilization of the simulator envelope, while reducing the need for parameter tuning. The PBMC algorithm was compared to a classical filter-based approach in an experimental study. To allow for a robust and reliable comparison, an evaluation method for motion cueing algorithms (MCAs) based on psychophysical techniques was developed. Results show that the PBMC approach received significantly higher ratings than the filter-based approach. This demonstrates the potential of the PBMC approach to improve motion cueing in vehicle simulation.*

Keywords: *driving, simulation, motion, cueing, evaluation*

Introduction

Recent technological developments concerning vehicle models, control loading, and quality of the visual and auditory stimuli have led to a considerable improvement in quality and realism of motion simulations. One aspect of motion simulation where major improvements are still to be achieved is motion cueing.

Motion cueing is the process of converting a desired physical motion of a vehicle (or vehicle model) into motion simulator input commands. This conversion is done by a motion cueing algorithm (MCA). As a motion simulator is limited to move within a confined space, vehicle motion can typically not be reproduced fully. Successful simulation therefore requires motion cueing 'tricks', which are implemented in the MCA. Designing and executing such tricks is what we refer to as the 'motion cueing challenge'.

The motion cueing challenge can be solved in different ways. Over the decades, many different types of MCAs have been introduced [Gar10]. The vast majority of them are variations of the "filter-based" approach, which relies mainly on scaling down and filtering the physical motions such that the result "fits" within the limited motion envelope of a simulator. Well-known characteristics of the filter-based approach are *tilt-coordination* (where low-frequency components of the linear acceleration are reproduced by tilting the simulator platform) and *motion washout* (the ever-present push to return to the initial position). The filter-based approach is therefore also known as a washout MCA.

There are several limitations to the filter-based MCA approach [Gar10]. For example, there is only *limited consideration for perceptual factors*. Mismatches between the expected perception and induced perception decrease the perceived realism of a simulation and can lead to simulator sickness. Although some filter-based MCAs do take some perceptual factors into account (e.g., tilt-rate thresholds for tilt-coordination), there still exists a large gap between the available knowledge about human self-motion perception and how much of this knowledge is implemented in motion simulation. Another known weakness of filter-based approaches is the need for *extensive parameter tuning*: parameter tuning is often required to adapt an MCA's properties to fit the needs of the simulation at hand. Determining the optimal value for each parameter is a difficult, time-consuming and subjective job, which can only be executed by experienced operators. In addition, the truly optimal parameter values depend on simulator state and the maneuver characteristics, and thus vary over time. Some algorithms allow parameter values to vary during the simulation, which introduces additional challenges such as the definition of the adaptation rules and the algorithm's stability. Finally, another well-known weakness of filter-based MCAs is the *limited use of simulator potential*. The tuning of an MCA is typically done using a "worst case"-scenario, such that the worst

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(largest) expected motion still fits within the motion space of the motion simulator. As a result, the physical simulator envelope is not always fully exploited.

In an attempt to mitigate some of the problems associated with the filter-based MCAs, this paper proposes an alternative approach: perception-based motion cueing (PBMC). A key difference with the traditional approach is that PBMC operates by optimizing the simulator input commands based on the output of a model of human self-motion perception, (or perception model in short). This allows for exploiting the idiosyncrasies of human perception.

Similar algorithms that make use of motion perception models, optimal control or model-predictive control approaches have been proposed in literature (e.g., [Siv82], [Tel05], [Dag09], [Ami12], [Beg12]). A comparison between the different approaches proposed for both driving and flight simulation would be insightful, but such a comparison will not be pursued in the current paper. The research question that will be addressed in the current paper is whether the motion cueing quality that PBMC provides is higher compared to the traditional filter-based approach. This immediately raises the question how the quality of an MCA can be measured and compared. A method was developed to that end, which will also be described.

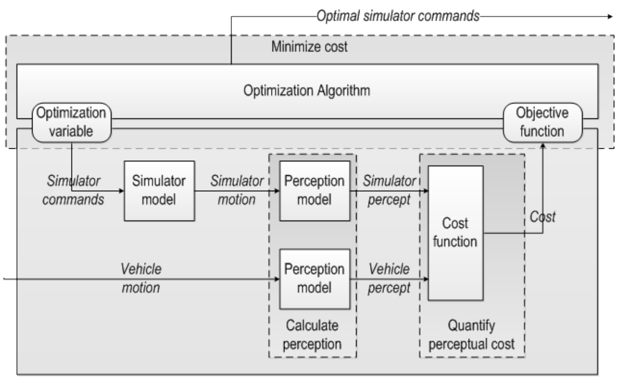


Figure 1: schematic representation of the perception-based motion cueing approach (PBMC)

Perception-based motion cueing

Figure 1 illustrates the workings of the proposed PBMC approach. The input to the algorithm is the vehicle motion that is to be simulated. The PBMC approach makes use of a perception model that mimics the perceptual process in the brain to calculate the driver's motion perception resulting from vehicle motion: the vehicle percept. The aim of PBMC is to reproduce this percept as closely as possible in the simulator. Using a simulator model and a perception model, it is possible to calculate the percept resulting from any set of simulator input commands: the simulator percept. The magnitude of the difference between the vehicle and simulator percepts is the “cost” associated to the simulator input commands, which is computed by the cost function. This cost function can be based on perceptual knowledge regarding, e.g., the relative importance of missing or false cues in different degrees of freedom. The optimization algorithm computes the set of simulator input commands that provides the minimal cost and thus reproduces the vehicle percept in the best possible way.

Simulator model

The simulator model serves two purposes. First, it is used to compute the simulator motion, i.e., the motion of the driver’s head in response to simulator input commands. Second, the simulator model provides information regarding workspace constraints. In other words, it specifies which dynamical states the simulator can reach at any given instant in time. Information on the state and workspace constraints of the simulator is absent in many traditional MCAs. For those MCAs, simulator limits are avoided by carefully tuning the parameters and by limiting actuators commands. Still, it can and does happen that the simulator cannot execute the commands as they are provided by the MCA, because it would cause one or more actuators to exceed a position, velocity or acceleration limit. The use of a simulator model in the MCA eliminates this issue. In addition, it improves the utilization of the simulator envelope, as the MCA has direct access to the simulator’s physical affordances and constraints at all times.

Human self-motion perception model

A perception model is a computational model that describes how human sensory organs translate physical stimuli into internal representations and how these are then processed by the brain to result in conscious perception (or: percept).

Rotational velocities and specific forces are sensed through the vestibular system, consisting of the semi-circular canals and the otoliths. In addition, visual information (i.e., optical flow) is received through the eyes, from which information can be extracted regarding linear and rotational velocities and orientation with respect to gravity. The perception model therefore has two classes of inputs: vestibular inputs and visual inputs. These inputs combine into the three main components of the perceived motion: rotation, translation and orientation.

The perception model used in this study is based on the model described by Newman et al. [New12] and describes sensory dynamics and visual-vestibular sensory integration. This model was chosen in this study because it is well validated and more advanced than what is used in previous

PBMC approaches [Tel01]. Note, however, that the PBMC approach offers a general framework that is independent of the perception model itself, and so other perception models can be used.

Cost function

The simulator percept and the vehicle percept are both multidimensional quantities consisting of perceived rotation, translation and orientation with respect to gravity. The difference between these two percepts is quantified by the cost function.

The cost function used in this study computes the sum of the squared Euclidian distances between each perceptual dimension:

$$C(t) = \sum_{i=1}^{N} K_i(\Psi_v^i(t) - \Psi_s^i(t))^2 \qquad (1)$$

Where:

$C(t)$ is the cost function output
N is number of perceptual dimensions
K_i is the weight assigned to the i-th perceptual dimension
$\Psi_v^i(t)$ is the i-th dimension of the vehicle percept
$\Psi_s^i(t)$ is the i-th dimension of the simulator percept

The weights K_i were based on the inverse of perceptual threshold values obtained from literature (see, e.g. [Nes14]). The output of the cost function is a vector, which was converted to a scalar value by integrating the cost over time and dividing by the number of time samples.

The cost function used in the present study is very simple. More advanced cost functions are likely to increase the quality of the cueing considerably, e.g., by accounting for varying sensitivity of the perceptual system and/or by differentiating between different types of cueing errors. Such cost functions are currently being developed and tested.

Maneuver-based optimization

In the current study, the PBMC algorithm was applied to recorded maneuvers. Hence, all information about the maneuver is available to the MCA such that the optimization can be performed for all time steps of the maneuver simultaneously. This type of optimization is referred to here as “maneuver-based” optimization and is expected to provide the best possible motion cueing quality, as the algorithm has full access to the maneuver information.

This raises the question how the cueing quality would be affected if the available information is limited, as is in the case in real-time, closed-loop motion simulations. In such cases, it is required to make predictions about the future state of the simulated vehicle based on previous and current states. This approach is referred to in this paper as “horizon-based” optimization and makes use of model predictive control (MPC) techniques [Dag09, Beg12]. In these algorithms, the vehicle state is predicted up to a certain prediction horizon, for which the simulator commands are optimized. After optimization, a subset of the optimized simulator inputs (typically only the commands for the next time step) is provided to the simulator.

Two challenges in horizon-based optimization are obtaining reliable predictions of future vehicle states and choosing an appropriate prediction horizon. Although these challenges are largely outside of the scope of the current paper, they were partially addressed in the experiment by comparing maneuver-based optimization with horizon-based optimization. More details are provided in the section below.

Experimental validation

To test the PBMC approach an experiment was performed. Next to validating the PBMC approach, the experiment also served to test a novel evaluation method – using magnitude estimation – that was developed for this purpose.

Magnitude estimation

Evaluating the quality of an MCA through human-in-the-loop experiments is a complex task, as it inevitably involves recording subjective judgments that are affected by many factors, such as expectations, memory, personal preferences, experience and familiarity with the rating task.

In this study, the quality of the MCAs was evaluated using a magnitude estimation task with a cross-modality matching paradigm. This method was originally introduced by Stevens to measure the perceived magnitude of physical intensities [Ste56]. Other applications of this method can be found in [Lod75, Lod81, Han94, Bar96]. To the best of our knowledge, the magnitude estimation method has not yet been applied in the field of motion simulation research.

In the experiment, two response modalities were used by the participants to express the magnitude of perceived quality of motion cueing: numerical estimate and line production. The numerical estimate consisted of a written numeric value of a preferred magnitude, relative to the overall perceived quality of the cueing; the line production consisted of hand-drawing a horizontal line of a preferred length, relative to the overall perceived quality of the cueing. Using magnitude estimates from two response modalities enabled us to test the internal validity of the measurement scale: if the participants in the experiment are indeed rating the motion quality on a ratio scale, this should result in consistent answers across the two different modalities. For a detailed description of cross-modality matching as a subjective assessment technique, the reader is referred to [Pep83].

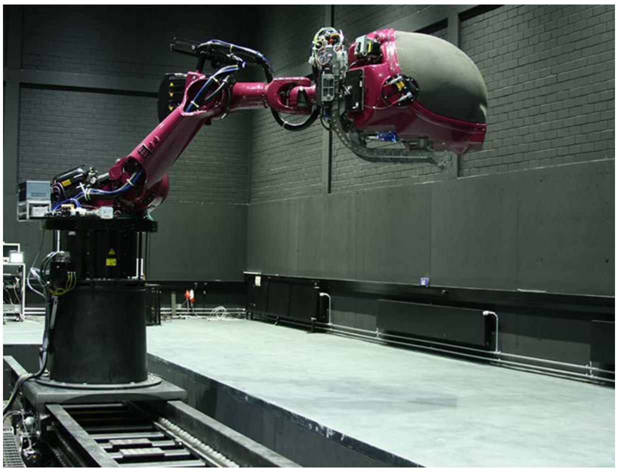


Figure 2: the CyberMotion Simulator (CMS) of the Max Planck Institute for Biological Cybernetics

Apparatus and participants

The experiment was conducted on the CyberMotion Simulator of the Max Planck Institute (MPI) for Biological Cybernetics (Figure 2, [Nie13]).

Data was collected for 10 participants, recruited through the MPI's participant database. Upon signing-up for the experiment, participants declared to hold a full and valid driving license for cars and to perform active driving on a regular basis. They had normal or corrected-to-normal vision. All participants provided informed written consent prior to participation. The study was conducted in accordance to the Declaration of Helsinki (1964).

The data of one subject was rejected based on the correlation criterion (explained below). Data analysis was performed for the remaining 9 participants (average age: 27.0 year, standard deviation: 4.0 year, one female).

Experimental procedure

The experimental procedure consisted of three phases: the calibration phase, the experiment phase and the verbal qualification phase.

Calibration phase

In the calibration phase, participants were familiarized with the magnitude estimation method. After receiving a written instruction, they were presented with printed lines of varying length and were asked to assign numerical estimates to their length. Directly after that, they were presented with printed numerical values of varying magnitude and were asked to draw horizontal lines whose lengths were proportional to the numbers' magnitudes. This procedure served primarily to familiarize the participant with the task they were to perform during the experiment phase. In addition, this procedure served to determine whether participants were actually capable of producing consistent magnitude estimates across different response modalities.

Experiment phase

In the experiment phase, participants were seated inside the CyberMotion Simulator (CMS) and exposed to combinations of driving maneuvers (e.g., slalom, acceleration-deceleration) and MCAs (e.g., filter-based, PBMC). The driving maneuvers and MCAs are described in detail in the next sections. A combination of a maneuver with an MCA will be referred to as *a trajectory*.

During each trajectory the participant was instructed to pay particular attention to the motion information ("what you feel") and how it related to the visual information ("what you see"). After each trajectory the simulator came to a smooth stop after which the participant rated the overall goodness of the motion simulation using the magnitude estimation method. Both the numerical estimate and line production should be proportional to the impression of the overall goodness of the motion cueing.

Before the actual rating task started, each participant was presented with several training trajectories. The maneuver that was used in these trajectories (a parabolic curve at constant speed) was not used during the experiment. The data of the training trajectories was excluded from the analysis.

During the experiment, the trajectories were grouped per maneuver, i.e., a participant experienced the trajectories for each MCA for one maneuver before moving to the next maneuver. This blocking approach made the rating of the relative quality of different MCAs for a maneuver more reliable. The participants were instructed to provide any line length/positive number for their first response, keeping in mind that they might want to provide longer/shorter lines and larger/smaller numbers later on. The participant could see their responses given for previous trajectories of the same block. Participants were encouraged to be as consistent as possible with their ratings between blocks. The presentation order of the maneuver blocks and trajectories within each block was randomized.

During the experiment, the level of motion sickness was closely monitored. The experiment was terminated as soon as mild motion sickness symptoms arose.

Verbal qualification phase

In order to interpret the meaning of the collected ratings, use was made of verbal qualifiers (VQs) [Roh07]. After the experiment phase, participants were asked to rate the perceived magnitude of a set of VQs using the same rating method as during the experiment phase. The VQs were "terrible", "very bad", "bad" "somewhat bad", "so-so", "somewhat good", "good", "very good", and "excellent". The goal of this procedure was to obtain a verbal interpretation of the ratings obtained in the experimental phase. As participants may differ greatly in the rating magnitudes awarded to different levels of simulation quality, this strategy allowed us to map subjective ratings provided by different participants to a common scale.

The VQs were presented in random order, starting with “so-so”. The participants were instructed to use similar number magnitudes and line lengths as they used during the experiment phase.

Maneuver stimuli

The driving maneuvers were generated using car simulation software CarSim (Mechanical Simulation). This software simulates and animates the dynamics of a chosen car model, calculating realistic physical output depending on a given control input. The simulated car was a mid-size Sedan with a 160kW engine and 6 gears. The width of the road for all maneuvers was 14m.The maneuvers were the following (name in bold):

- **AccDec**: acceleration from 0 to 100 km/h in approximately 10 seconds. Constant velocity for approximately 5 seconds. Deceleration to 0 km/h in approximately 9 seconds.
- **LaneChange**: an ISO 3888-1:2009 double lane-change maneuver at constant speed (50 km/h).
- **Slalom**: a slalom maneuver, consisting of 11 yaw reversals at a constant speed of 40 km/h. The cones were placed at a distance of 18 meters, and the slalom trajectory had an amplitude of 1.5 m.
- **Uturn**: a 180 degree (30m radius) curve maneuver at constant speed (50 km/h).

The following maneuver was used for training:

- **Parabola**: a parabolic curve at constant speed (70 km/h).

For each maneuver other than AccDec, the maneuver was preceded by a smooth acceleration to the target velocity and ended with a smooth deceleration to 0 km/h. The start and end of each maneuver was indicated through blue lines and cones on the road. Participants were instructed to only rate the sections delimited by the blue lines.

Motion drive algorithms

Four MCA were compared: one filter-based MCA (referred to as “Classical”) and three versions of the PBMC algorithm (referred to as “FPMman”, “NPMman”, “NPMhor”). The reason for including different versions of the PBMC algorithm is to gain insight into the separate effects of introducing a perception model and the prediction horizon.

Perception-based MCAs

The PBMC algorithm described previously will be referred to as “FPMman”, where “FPM” stands for “full perception model” and “man” for “maneuver-optimization”. Recall that maneuver optimization refers to optimizing the simulator commands for all time steps simultaneously, by providing the vehicle states of the complete maneuver to the algorithm.

Clearly, the PBMC algorithm is radically different from the filter-based approach. When comparing the two, it is important to understand whether differences should be attributed to – e.g. – the use of a perception model or to the optimization of the simulator inputs. In other words, it is important to obtain an insight in how the individual features of the PBMC algorithm contribute to the quality of the motion cueing. In order to provide this insight, two additional variations of the PBMC approach were included in the experiment. The first is referred to as the “NPMman”, where “NPM” stands for “no perception model”. In this MCA, the perception model (see Figure 1) was replaced with a set of unity gains. As a result, the input for the cost function changed to the vehicle motion and simulator motion and the cost reflected the difference between the physical motion of the vehicle and simulator. By comparing the FPMman with the NPMman, the effect of including a perception model could be investigated.

In order to investigate the effect of maneuver-optimization against the more practically relevant horizon-optimization, a prediction horizon was introduced. In this condition, only 2.5 seconds of the future vehicle motion was provided to the algorithm. After an optimization step, the simulator commands of the next time step were used, the results for the remaining time steps were used as initial values for the next optimization step. In this fashion, the optimization was done for each time step sequentially, instead of for all time steps simultaneously. This MCA is referred to as “NPMhor”, where “hor” stands for “horizon-optimization”. Note that also in this MCA no perception model was present and the prediction is a ‘perfect’ prediction. The reason for employing this ‘perfect’ prediction here is to avoid introducing the prediction strategy as a factor influencing cueing quality.

Classical MCA

The structure of the classical MCA is indicated in Figure 3. This structure is similar to the MCAs described in [Rei85] and [Gra96] and is representative for what is currently used in many motion simulators.

The algorithm’s parameters were tuned for each maneuver separately using an automatic tuning procedure, analogous to the PBMC algorithm. The simulator model in Figure 1 was replaced by the classical MCA including the inverse simulator kinematics and the simulator model. The optimization variable was changed from simulator input commands to the parameters of the classical

MCA. During the optimization of the classical MCA the NPM was used as perception model, to make the procedure representative for the fact that classical MCAs are often tuned by reducing the difference between physical vehicle and simulator motion and not their percepts.

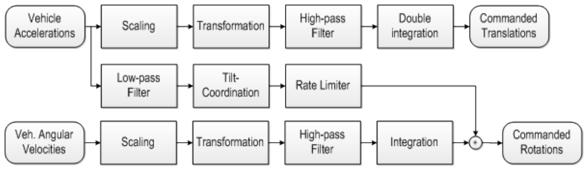


Figure 3: structure of filter-based MCA ('Classical')

Independent and dependent variables

The independent variables in this experiment were the maneuvers (4 levels: AccDec, LaneChange, Slalom, UTurn) and the MCAs (4 levels: Classical, FPMman, NPMman, NPMhor). This results in 16 trajectories.

The dependent variables recorded during the experiment were the numerical estimates and hand-drawn lines for each of the conditions. In addition, calibration and verbal qualifier data were recorded for each participant and a simulator energy metric (explained below) was computed for each trajectory.

Analysis

Correlation criterion

The measurements obtained in calibration phase served to determine whether participants were actually capable of producing consistent magnitude estimates across different response modalities. In order to qualify for participation in the experiment phase a correlation criterion had to be satisfied, consisting of the Pearson product-moment correlation coefficient (also known as correlation coefficient R) between the numerical values and line lengths, which had to be larger than 0.95. All 10 participants met the correlation criterion for the calibration phase data. The correlation criterion was applied post-hoc to the data from the experiment phase and verbal qualifier phase. One participant did not meet the correlation criterion in the experimental phase and hence was excluded from the analysis.

Standard score

After digitizing the written responses obtained in the experiment phase, the data was analyzed per participant. The results from the numerical estimate (NE) and line production (LP) were normalized and then averaged, using:

$$S = \frac{1}{2}\left(\frac{NE-\mu_{NE}}{\sigma_{NE}} + \frac{LP-\mu_{LP}}{\sigma_{LP}}\right) \qquad (2)$$

Where:

S is the normalized standard score

NE / LP is a NE/LP response
μ_{NE} / μ_{LP} is the mean of the NE/LP responses
σ_{NE} / σ_{LP} is the standard deviation of the NE/LP responses

Verbal qualifiers

The NE and LP responses obtained for the verbal qualifiers for each subject were used to obtain a standard score for each participant using Eq. 2. By averaging the standard scores across participants, the average verbal qualifiers were obtained.

Simulator energy metric

In order to compare the MCAs in terms of the amount of simulator motion it produces, a simulator energy metric was defined and computed for each trajectory. This energy metric consists of the sum of the integrated specific kinetic energy of each of the eight simulator axis:

$$E_{sim} = \sum_{i=1}^{8} \int \frac{1}{2} v_i(t)^2 dt \qquad (3)$$

Where:

E_{sim} is the simulator energy metric
$v_i(t)$ is the velocity of the i-th axis

Results

The overall results of the experiment are presented in Figure 4. The figure shows the average rating across participants and maneuvers, for each MCA. The spread is indicated by the standard error of the mean. A repeated measures ANOVA shows a significant effect of MCA ($F(3,128)=19.18$, $p<.05$), no significant effect of maneuver ($F(3,128)=1.41$, $p=.24$) and no interaction between maneuver and MCA ($F(9,128)=1.69$, $p=.10$). Paired comparisons show that all three implementations of the PBMC approach received a significantly higher rating than the classical MCA. The ratings for the PBMC approaches did not significantly differ from each other.

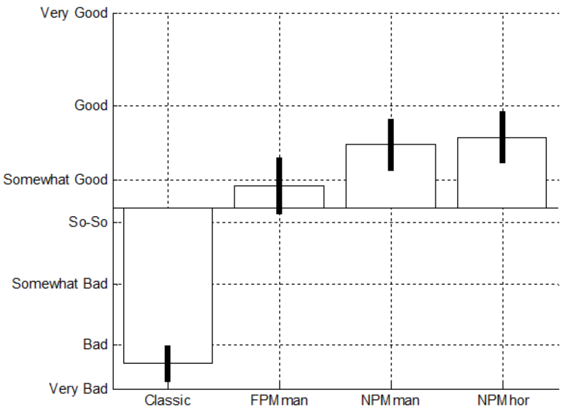
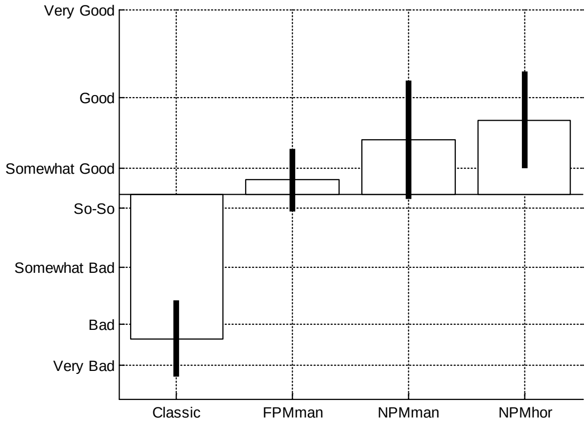
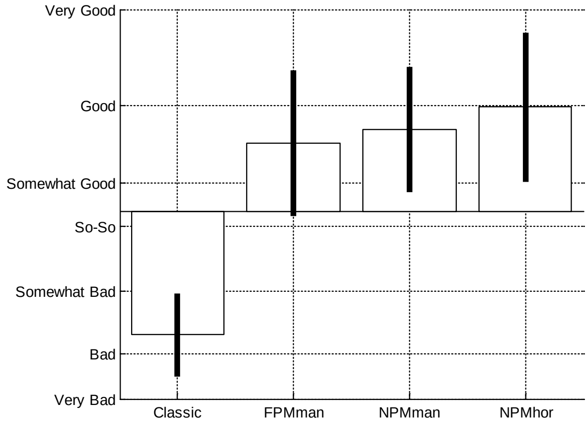


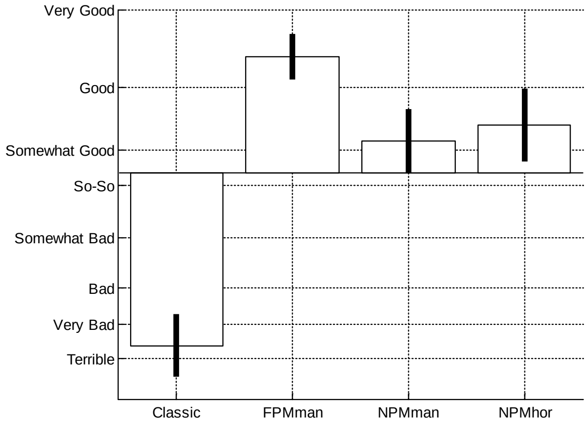
Figure 4 : Results of a comparison between a traditional, filter-based MCA ("Classic") and the three implementations of the PBMC approach. The bars show the average across maneuvers and subjects. The spread is indicated by the standard error of the mean.



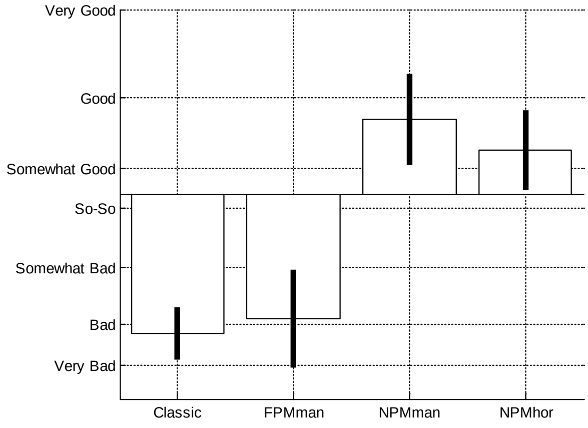
a) Results for AccDec maneuver



b) Results for LaneChange maneuver



c) Results for Slalom maneuver



d) Results for UTurn maneuver

Figure 5 : Rating results for individual maneuvers. The bars show the average across subjects. The spread is indicated by the standard error of the mean.

Figure 5 shows the results obtained for each individual maneuver. Rather consistent results were obtained for the classical MCA, which received poor ratings for each maneuver. The FPMman MCA shows a poor rating in one maneuver (UTurn) and a good rating in another maneuver (Slalom). The other two MCAs show results that are fairly consistent across conditions.

Figure 6 shows the average energy metric (Eq. 3) against the average rating for each MCA (note that here the numerical ratings are shown, not the VQ). The horizontal and vertical lines indicate the standard error of the mean for the rating and energy metric respectively. From this figure it becomes clear that the cueing provided by the NPMman MCA leads to significantly higher simulator axis velocities than are obtained for the other MCAs. This is not necessarily a disadvantage, especially not if it leads to higher ratings. Interestingly, however, the figure shows that the energy metric for the FPMman and NPMhor MCA are significantly lower, while the ratings are not significantly different. This indicates that the FPMman and NPMhor MCA were able to reproduce the maneuvers with a similar perceived quality at a much lower expense of simulator energy.

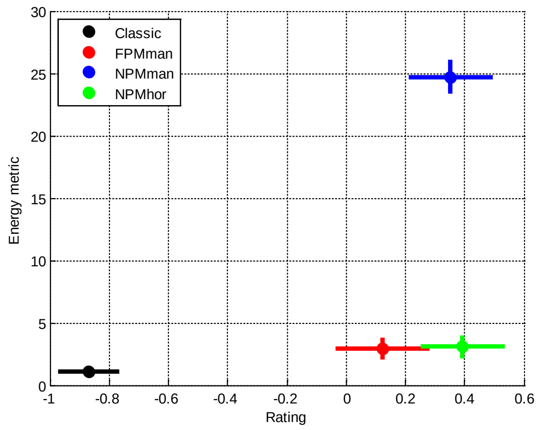


Figure 6: Rating versus energy metric. The dots indicated the mean of ratings and energy metric values across maneuvers for each MCA. Error bars indicate SE of mean.

Conclusions

The results show that:

- there was a clear and consistent preference for the PBMC algorithms over the filter-based MCA;
- the quality ratings for the PBMC algorithms did not vary significantly from each other;
- removal of the perception model significantly increased the simulator axis velocities, without significantly increasing the quality ratings;
- the simulator axis velocities were also significantly reduced by a reduction in prediction horizon.

These results allow for the following general conclusions: overall, the PBMC algorithms were preferred over the filter-based MCA. A comparison of the PBMC algorithms showed that inclusion of the perception model and reduction of the prediction horizon did not noticeably decrease the quality of the cueing. However, an energy analysis showed that PBMC algorithms that made use of a perception model and reduced prediction horizon required significantly less energy, without affecting perceived cueing quality.

The evaluation method that was used in this study – magnitude estimation with cross-modality matching – has shown to provide a fairly robust and reliable indication of MCA quality. That is all the more remarkable as this experiment was performed by non-expert participants, who had very little experience with motion simulation, if any at all. The magnitude estimation paradigm has several advantages over alternative methods, of which the most important are the high resolution, the absence of scale boundaries and the fact that the data is measured on a ratio scale which allows for statistical analysis. Finally, the approach requires significantly less trial repetitions than some other methods that produce ratio scale data, such as paired comparisons. Overall, the proposed evaluation method showed to be a useful alternative or companion to existing evaluation methods.

Discussion

Perception-based motion cueing can increase the realism of motion simulation due to several factors. The perception model provides information on how vestibular and visual stimuli are perceived and integrated into a percept of motion, which allows for exploiting the limitations and ambiguities of human perception. As our understanding of human self-motion perception progresses further, the benefits of including a perception model will only increase. The simulator model provides information on the state and constraints of the simulator, which allows for making more optimal use of the simulator's capabilities. As a result, PBMC explicitly accounts for actuator limits and can therefore provide cueing that approaches or reaches these limits, without ever exceeding them. Furthermore, by optimizing the simulator inputs based on current and future (predicted) information, the resulting cueing is optimal in terms of perceptual cost. Finally, the PBMC algorithm requires almost no tuning of parameters, which is a large advantage over many traditional approaches.

The main disadvantage of the PBMC over filter-based MCAs is the relative complexity of the algorithm, which inevitably impacts the speed at which the algorithm operates. At the time of writing, real-time simulations have not yet been achieved. Real-time simulations were not required for the purposes of the current comparative study. However, for many practical motion cueing applications, real-time execution is essential. In order to achieve this, the implementation of the PBMC algorithm is currently being further optimized for speed performance.

Another disadvantage of the PBMC algorithm is that, by the continuous optimization process, the way in which the inputs are processed can vary over time. As a result, identical consecutive motions may be cued differently by the PBMC algorithm. This in contrast to filter-based approaches, where the input processing does not vary over time. In some applications, the consistency of the cueing is of larger relevance than the achievable cueing quality. More research is required to determine how large and how problematic the variability in cueing quality is for PBMC approaches.

The fact that the classical MCA consistently received a very poor rating compared to the PBMC alternatives can be interpreted as evidence that the PBMC approach is a promising alternative for motion cueing. It should be noted, however, that it is possible that the tuning of the Classical MCA can be further improved. The automatic tuning approach that was used in this study resulted in simulator behavior with typical filter-based MCA characteristics, such as significant input scaling and considerable tilt-coordination. A careful and time-consuming manual tuning could possibly have increased the cueing quality and the ratings. It is unlikely that even an optimal tuning would have made up for the large difference in ratings that were found in this study, although that possibility cannot be excluded. Comparisons with a classical MCA that was carefully tuned by an independent expert, would provide more conclusive evidence.

For the FPMman MCA the quality ratings varied between different maneuvers from very positive to very negative. The difference between the ratings for the Slalom and UTurn maneuver deserve closer investigation. What differentiated the cueing of the two maneuvers to result in such a large difference in appreciation by the participants? Definitively answering this question requires an analysis that would take up more space than is available here. An initial analysis suggests that a possible explanation may lie in how the sustained lateral force in the Uturn was generated by the FPMman MCA: a combination of lateral translation and roll accurately reproduced the lateral forces, but also introduce a significant roll error and a sustained tilted position for the duration of the turn. Interestingly, a similar combination of translation and roll was used to reproduce the lateral forces in the slalom maneuver, which received a good rating. Possibly, the fact that the tilt in the Uturn was sustained severely impacted the quality of the cueing for that maneuver, which could hint towards a possible way the cost function could be improved.

The significant difference in the energy metric is a relevant finding. The larger energy metric values correlate with larger motion space usage, requiring a larger motion simulator. It would be interesting to also investigate other, possibly more general ways of defining the simulator energy metric, e.g., by considering normalized peak actuator displacement, but this is left for future work.

As the CMS is a relatively large motion simulator with a large planar motion space, the simulator was capable of approximating the physical vehicle motion fairly well. On smaller systems or systems with a different architecture, such as hexapods, this would no longer be the case, which would increase the need for selecting the optimal motion strategy by carefully balancing relative importance of false and/or missing cues in various degrees of freedom. It is to be expected that the benefits of including a full-fledged perception model and an extensive cost function will come to further fruition in such conditions.

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