Chapter 9
Perception-Based Motion Cueing: A Cybernetics Approach to Motion Simulation

Paolo Pretto, Joost Venrooij, Alessandro Nesti, and Heinrich H. Bülthoff

Abstract The goal of vehicle motion simulation is the realistic reproduction of the perception a human observer would have inside the moving vehicle by providing realistic motion cues inside a motion simulator. Motion cueing algorithms play a central role in this process by converting the desired vehicle motion into simulator input commands with maximal perceptual fidelity, while remaining within the limited workspace of the motion simulator. By understanding how the one's own body motion through the environment is transduced into neural information by the visual, vestibular and somatosensory systems and how this information is processed in order to create a whole percept of self-motion we can qualify the perceptual fidelity of the simulation. In this chapter, we address how a deep understanding of the functional principles underlying self-motion perception can be exploited to develop new motion cueing algorithms and, in turn, how motion simulation can increase our understanding of the brain's perceptual processes. We propose a perception-based motion cueing algorithm that relies on knowledge about human self-motion perception and uses it to calculate the vehicle motion percept, i.e. how the motion of a vehicle is perceived by a human observer. The calculation is possible through the use of a self-motion perception model, which simulate the brain's motion perception processes. The goal of the perception-based algorithm is then to reproduce the simulator motion that minimizes the difference between the vehicle's desired percept and the actual simulator percept, i.e. the "perceptual error". Finally, we describe the first experimental validation of the new motion cueing algorithm and shown that an improvement in the current standards of motion cueing is possible.

Keywords Motion cueing • Motion perception • Self-motion • Simulation • Model predictive control • Washout

When we move through the environment, our central nervous system (CNS) is called upon to create a continuous estimate of the state of our own body with respect to the world (i.e. its position, orientation and their derivatives). This perceptual process,

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S.-W. Lee et al. (eds.), *Recent Progress in Brain and Cognitive Engineering*,
Trends in Augmentation of Human Performance, DOI 10.1007/978-94-017-7239-6_9

generally referred to as self-motion perception, plays a crucial role in vital tasks such as balance and locomotion. Not surprisingly, considerable research efforts have been devoted to further our understanding of how the CNS integrates available sensory information to create an internal representation of the physical bodily motion [7, 21]. These studies have provided great insight into how physical stimuli are transduced into neural information by the visual, vestibular and somatosensory systems and how this information is processed in order to create a percept of self-motion. From experiments on human perception, theories and models are developed and continuously improved, which have as ultimate goal to provide accurate descriptions of the perception of the complex motion patterns experienced in everyday life.

A widely employed approach to the study of self-motion perception is the so called Cybernetics approach. The term "Cybernetics" generally refers to the study of those systems able to generate changes in their environment which, in turn, are fed back to the system, altering its status and influencing future actions [39]. When applied to perception, the Cybernetics approach considers the brain of biological organisms as a complex control system where subcomponents can be isolated and individually investigated. Experimental methods such as psychophysics are employed to quantify the properties of human self-motion perception. Modelling methods rooted in system theory are used to model how the brain infers a representation of the physical world from sensory signals and generates actions to successfully interact with it. In this perspective, the Cybernetics approach, the psychophysical methods and behavioral measurements described in this chapter are powerful tools for Cognitive Engineering to investigate the fundamentals of perceptual and cognitive processes. The use of simulation technologies enables the implementation of these fundamental processes in control algorithms and improves the current understanding of human perception and action.

The study of self-motion perception is of great benefit for a wide variety of fundamental but also applied fields. For example, it is of use for the development of perceptual tests for clinical diagnosis and rehabilitation of patients with balance disorders [1, 20]. In this chapter, we focus on a different, but equally practical application: we will address how a deep understanding of the functional principles underlying self-motion perception can be exploited to develop new algorithms for motion simulators.

Motion simulators are widely employed in many different applications, such as training, research and development and entertainment. Despite large differences in architecture, complexity and purpose, all motion simulators have one aspect in common: the use of a Motion Cueing Algorithm (MCA), also known as motion drive algorithm. The MCA is responsible for converting a desired physical motion into commands that are sent to the motion simulator. In this chapter, we will explore how the design of MCAs can benefit from fundamental knowledge on self-motion perception and, in turn, how motion simulation can increase our understanding of brain perceptual processes.

9.1 Self-Motion Perception and Vehicle Simulation

With the progress in science and technology, the use of simulations of human controlled tasks became more and more common. This not only thanks to the increased fidelity of such simulations, but also to the effectiveness of training, studying, entertaining, or otherwise involving humans in simulations. A common application of simulation is vehicle simulation, where the manual control of a vehicle such as an aircraft, car or ship is simulated. Such simulations typically include control devices similar to the control devices in the actual vehicle and a visual projection from the point of view of the driver or pilot of the simulated vehicle. In some cases, the simulation includes motion cues, provided to the human operator through a motion platform (such as a hexapod motion simulator). The goal of including motion cues is to increase realism of the simulation by providing additional cues to the human operator. This type of vehicle simulation is referred to as *motion-based simulation* or, in short, motion simulation.

In motion simulation, any reproduction of a simulated maneuver on a motion simulator is always constrained by the physical limits of the motion system. For example, maneuvers that involve high sustained accelerations, such as the take-off of an airplane, make the simulator reach its physical limits eventually. At this point, the pilot inevitably experiences a conflict between the expected and experienced motion. This has several potential drawbacks such as the occurrence of motion sickness, an overall degrade in simulation realism and the occurrence of "false training", i.e., when pilots learn to react in a way that is not appropriate for the simulated maneuver.

As the quality of a motion simulation is eventually determined by the simulator user, based on how well the desired perception of motion is reproduced, it should be evident that knowledge on self-motion perception is beneficial, if not a prerequisite, in the development and evaluation of MCAs. However, there is a surprisingly large gap between what we know of human self-motion perception and how much of that knowledge is actually used in practice. In Sect. 9.3, we will explore how we can bridge this gap by using perception-based motion cueing. However, before doing so we need to describe more in detail the traditional approach to the motion cueing challenge.

9.2 The Motion Cueing Challenge

Technological advances in the field of vehicle simulation have mainly concerned the development of vehicle models, the visual rendering, control loading and quality of the auditory stimuli. Motion cueing, on the other hand, remains one aspect of motion simulation that has not benefited equally from technological advances, and still remains one of the main challenges when operating a motion simulator. In

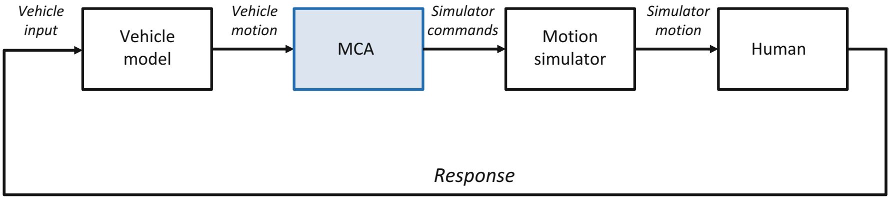

Fig. 9.1 The process of motion simulation. Vehicle motion provided by a model is converted into simulator commands by the MCA. The human (driver) experiences the simulator motion and reacts on the vehicle commands, changing the state of the vehicle model

fact, many state-of-the-art simulators are still employing MCAs that are not so different from those developed several decades ago, for simulators whose hardware and software are, today, obsolete.

Motion cueing can be defined as the conversion from desired motions to motion simulator input commands. For example, if one wants to simulate a car driving on a race track in a motion simulator, the output from a vehicle model can be used to compute the desired motion, expressed in, e.g., the accelerations and rotational rates of the car. An MCA processes this desired motion and calculates the appropriate motion simulator input commands – expressed in, e.g., position and velocity of the motion simulator's actuators (see Fig. 9.1). For instance, in case the simulation is executed on a hexapod simulator, where the actuators are six telescopic jacks, the MCA determines the input commands for each actuator at every simulation time step. From the above description it becomes apparent that an MCA needs to be tailored to the configuration and capabilities of the motion simulator hardware (e.g., number and configuration of its actuators). Next to that, the MCA is tailored to the vehicle that is simulated, the maneuver that the vehicle is performing and possibly even the person driving the simulated vehicle.

As the range of motions of a simulated vehicle, such as the car driving on the race track, is typically much larger than the motion range (or workspace) a motion simulator can cover, the MCA needs to ensure that its output commands are realizable by the platform. In order to provide a realistic simulation, even for maneuvers that are outside the motion simulator's workspace, several different approaches can be applied. In literature, different MCAs have been proposed, tested and compared. It is not the purpose of this chapter to provide an exhaustive overview of all of these algorithms, or even of the most important ones (see e.g. [8] for a concise overview). Instead, in the following we will sketch – in broad strokes – how motion cueing algorithms were initially conceived and what their limitations are. This helps to understand the context of the alternative approach to motion cueing that we will address in the next section.

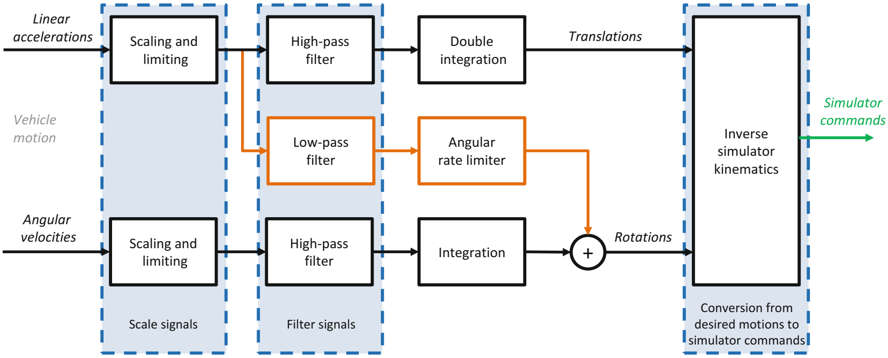

Fig. 9.2 Schematic representation of a CMCA

9.2.1 Classic Approach

The first MCA described in literature is what has become known as the "classical" algorithm. This approach was first described by Conrad and Schmidt [5] and later extended by Reid and Nahon [29–31]. In this chapter, this approach will be referred to as the Classical MCA (CMCA). The workings of the CMCA are illustrated in Fig. 9.2.

The desired motion is expressed in terms of linear accelerations and angular velocities. Both are (possibly) scaled and limited through saturation to account for the physical limits of the simulator. The results of this process are then high-pass filtered, which allows for the onsets of motions (high frequency signal) to be reproduced whilst removing the sustained accelerations and angular velocities, likely irreproducible within the simulator workspace. The output of the high-pass filter can be integrated to obtained, e.g., desired simulator position and simulator orientation. The application of filters (both high-pass and low-pass filters, as described below) is the hallmark of the "classical" approach.

In order to reproduce also the sustained low-frequency components of the acceleration, most CMCA use a procedure called tilt-coordination. Tilt-coordination exploits the fact that human acceleration sensors such as the otolith organs respond to the vector sum of gravity and inertial accelerations (i.e. the gravito-inertial vector). This can lead to an ambiguity between a static head tilt and a linear acceleration with the head upright [2]. Through tilt-coordination, the simulator cabin is tilted to align gravity with the gravito-inertial vector resulting from sustained accelerations. For example, when the body is tilted backwards the vestibular system receives inputs that are indistinguishable from when the body is accelerated forwards. This ambiguity is used in tilt-coordination to reproduce sustained longitudinal and lateral linear accelerations by pitch and roll rotations, respectively. To ensure that the perceptual ambiguity is resolved in favor of the perception of a translation rather than a physical tilt, visual cues congruent with linear self-motion are concurrently provided [11] and the tilt rate of the simulator cabin is maintained below the human perceptual threshold [13, 27, 36, 40]. The latter is done by limiting the rate at which the platform tilts, using an angular rate limiter. The tilt-coordination path of the classic MCA is indicated in Fig. 9.2 ("Angular rate limiter").

Next to the high-pass filters and the tilt-coordination, many CMCAs have an additional feature that continuously repositions the simulator towards the center of its operational workspace, i.e., towards the position where the simulator dexterity is highest. This is achieved by designing the high-pass filters such that the simulator always returns to its initial position. With these filter settings all simulator motions are 'washed out' over time. For this reason, CMCA are also referred to as washout filters or washout MCAs.

9.2.2 Limitations of Classic Approach and Evolution of MPC-Based Motion Cueing

Alternative approaches to the CMCA described above have been proposed in literature. Many of these, however, are variations and extensions of the CMCA approach, sharing therefore most of its problems and limitations. Among these, the most important are:

- Limited consideration for perceptual factors: Although several studies have shown that the human sensitivity to motion is influenced by factors such as stimulus characteristics and cognitive factors [23, 27, 33], these and many other insights into human self-motion perception are not included in currently used MCAs. A common issue in motion simulation that would immediately benefit from an increased consideration for perceptual factors is, for example, the relatively high rate of simulator sickness, cause by sensory conflicts [14].
- Need for extensive tuning: an MCA has a number of parameters that can be set to a desired value. Typically, the number of parameters is in the order of several tens but can sometimes be as high as a few hundreds. With these parameters, the behavior of the MCA can be adapted to better fit the needs of the simulator user, simulator architecture, simulated maneuver, etc. However, determining the best value for all parameters is a difficult job, making it an expensive and time consuming process, which can only be done by experts. Many simulator users do not have the expertise to improve the tuning of their MCA or adapt it for different maneuvers.
- Limited use of simulator motion envelope: the tuning of an MCA is typically done using a "worst-case" scenario, such that the worst (largest) expected motion still fits within the motion space of the motion simulator. This implies that the simulator capabilities are not fully exploited during normal operation.

The abovementioned problems are aggravated by the fact that no systematic method exists to evaluate the quality of an MCA. Many simulator users (e.g., airline pilot training centers, car manufacturers, research institutes, universities) would like to improve their MCAs but have no tools at their disposal to measure their quality. Even experts tuners have to rely on subjective judgments, for example from test drivers, in order to adjust the tuning. An objective, reliable and repeatable method of evaluating the quality of an MCA would be welcomed by the motion simulation community at large. In Sect. 9.4 a methodology that was developed by the authors to fill this gap is presented.

Over the years, several filter-based variations of the classical (washout) approach were implemented to improve MCAs by addressing one or more of the above problems. For example, in adaptive washout filters the parameters are tuned automatically through an optimization algorithm. Although this reduces the need for parameter tuning, it introduces a new problem, namely the definition of a cost function. The optimal solution is found by minimizing the value of this cost function [28]. A cost function also contains parameters, such as weights of cost elements, which require tuning. In the adaptive washout approach the problem of tuning is not removed, but merely relocated.

More recently, it was proposed to solve the motion cueing challenge using Model Predictive Control (MPC) [4, 6]. MPC is a process control strategy that relies on dynamical models of the process. The application of MPC to a driving simulation scenario requires models of the motion simulator and of the driver's perception. Simulator commands are then obtained by minimizing the perceptual error (mismatch) without exceeding the physical limitations of the simulator. The MPC approach optimizes at each time step the simulator commands for a finite time-horizon based on a prediction of the future. The commands obtained for the current time step (i.e., the first value of the control sequence) are used for controlling the simulator and the process is repeated at each subsequent time step. Note that, for offline optimization, the entire trajectory is known and there is therefore no need to develop and implement a predictor, nor to use a prediction horizon shorter than the duration of the entire trajectory. The benefits of MPC motion cueing are that the platform motion matches the vehicle motion for as long as possible and that simulator limits are explicitly taken into account, thus eliminating the need to tune the MCA for the worst-case motion. In the published implementations of MCA algorithms for motion simulation, the focus has been centered on obtaining a real-time implementation. For this reason, linear simulator models were implemented in MPC algorithms to reduce computational load. Similarly, linear models of human sensory dynamics were usually favored over nonlinear self-motion perception models. However, the MPC approach also allows for implementation of nonlinear models which better describe human self-motion perception and motion simulators with nonlinear dynamics.

9.3 Perception-Based Motion Cueing

The perception-based motion cueing (PBMC) approach is based on advanced MPC control strategies for nonlinear models, and differs from the traditional approach CMCA in several ways. The most important difference is that PBMC aims to reproduce the *perception* of motion, instead of reproducing physical motion. Another important difference is that PBMC operates through optimizing simulator input commands, instead of filtering the motion that is to be reproduced. This approach is being developed with the purpose of improving the control strategies of the simulator on one side, and the perceptual fidelity, realism and user experience on the other side.

9.3.1 PBMC Structure

Knowledge about human self-motion perception is included in the MCA and used to calculate how the motion of a vehicle is perceived by a human observer inside a simulator. The calculation is possible through the use of a self-motion perception model, which simulate the brain's motion perception processes. The model transforms the linear and rotational components of vehicle inertial motion into a corresponding "vehicle percept", i.e. the mental representation of vehicle motion in a "perceptual space" (Fig. 9.3). It is then possible to map any vehicle motion within the physical space into its corresponding vehicle percept in the perceptual space. Thanks to a simulator model, the same calculation can be done for any simulator motion, which has a corresponding simulator percept. It is therefore possible to predict how a certain motion (trajectory) in the actual simulator workspace would "feel" in its corresponding perceptual space. The goal of the PBMC approach is then to minimize the difference (mismatch) between the vehicle desired percept and the actual simulator percept, i.e. the "perceptual error" (Fig. 9.3). The PBMC approach makes use of an iterative optimization process to find the simulator motion that best approximates the perception one would have in the actual vehicle. This optimization process searches for the minimum cost of a so called "perception-based cost function".

In the PBMC approach, the self-motion perception model, simulator model, perceptual cost function and optimization algorithm are integrated in a software framework. In the followings a brief description of these components and their integration is provided.

9.3.1.1 Self-Motion Perception Model

A human self-motion perception model (in the following also referred to as perception model) is a computational model that aims to describe the continuous

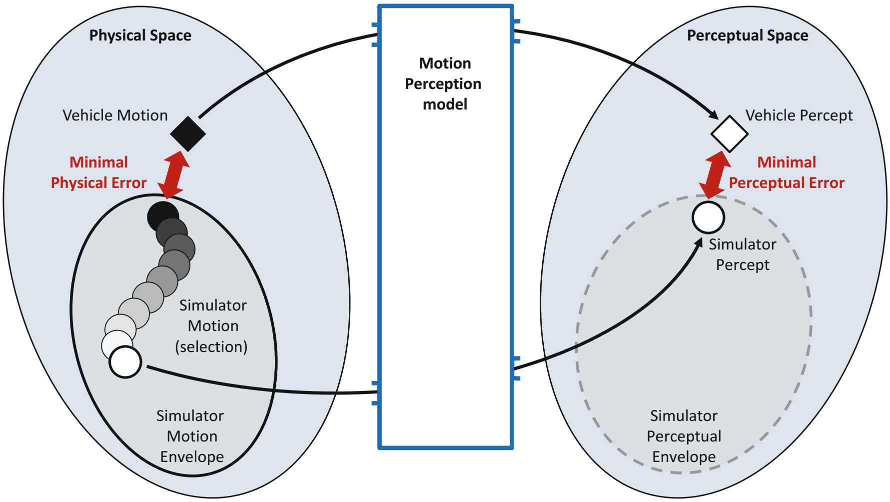

Fig. 9.3 Concept of the perception-based motion cueing

dynamical process taking place in the brain to produce a perception of motion through the environment. It does this by reproducing the way our sensory organs retrieve relevant information from the environment, and how these sensory signals are combined in the brain.

Physical motion is sensed by humans for a large part through the vestibular system, which is comprised of two components: the semicircular canals and the otoliths. These sensors respectively sense rotational motions (i.e., rotational velocities) and linear accelerations (i.e., specific forces). In addition, the eyes receive visual information (i.e., optical flow). The perception model has, therefore, two classes of inputs: *vestibular inputs*, i.e., rotational velocities and specific forces and *visual inputs*, i.e., motion information obtained through the visual sensors.

The first processing step of the perception model consists of reproducing the *sensory dynamics* of the perceptual organs. The next step constitutes the *sensory integration*, in which the different sensory information is combined into a single percept of motion. The third (optional) step accounts for the relative perceptual sensitivity to different stimuli, by transforming the physical units into perceptual units. This is done by applying psychophysical *perceptual laws*, which are nonlinear analytical functions that relate the intensity of the sensory input to the corresponding perceived intensity of motion [35]. This final step allows for the comparison of motion intensities within different degrees of freedom (e.g. rotations vs. translations) and accounts for nonlinearities in perception that are not related to the properties of the physical stimulation. For example, it is known that, for increasing motion intensities, the human sensitivity decreases in a nonlinear fashion [19, 22, 23]. The output of the perception model consists of a multi-dimensional *percept*: perceived motion described in perceptual units.

A perception model – and knowledge on human motion perception in general – can be beneficial for motion-based (vehicle) simulation applications in several different ways. For example, with a perception model one can determine how a given motion trajectory in a given simulator with a given MCA is perceived by the person inside the simulator. This gives indications with regards to whether the trajectory is reproduced realistically, which simulator provides a superior simulation and/or how the MCA – and/or the motion simulator – can be improved to increase the realism of the simulation.

9.3.1.2 Simulator Model

In PBMC, the simulator model serves two purposes: first of all, it is used to compute the simulator motion, i.e., the motion in response to simulator input commands. The accuracy of the simulator kinematics is essential, as the simulator motion is used to calculate the simulator percept, i.e., the perception that results from the given simulator motion.

The second purpose of the simulator model is to provide information regarding workspace constraints, in other words: which dynamical states the simulator can reach. Information on the state and workspace constraints of the simulator is absent in many traditional motion cueing approaches. This can, and often does, result in a situation where motion commands, sent to the simulator by the MCA, would cause one of the simulator's actuators to reach a position or velocity limit. Using a simulator model in the motion cueing approach avoids such issues. In fact, it allows for a more optimal use of the workspace that is available, as the simulator's capabilities are known at any given time.

9.3.1.3 Perception-Based Cost Function

The perception model provides two percepts: the simulator percept and the vehicle percept, which are both multidimensional quantities. The PBMC approach aims at minimizing the difference between these two percepts. The cost function is essential in achieving that goal. The cost function provides a measure for differences across the dimensions and weighs their relative contribution. Minimizing the cost function corresponds to minimizing discrepancies between vehicle and simulator motion (the "perceptual error" from Fig. 9.3). This provides answers to questions such as how much linear acceleration can be represented by tilting (tilt-coordination) or how much the simulator can be moved without the driver noticing the motion (subthreshold motions). Some traditional MCAs intend to incorporate some knowledge on human self-motion perception, for example, by limiting the maximum allowable tilt-rate. However, research has shown that sensitivities to motions vary with factors such as the presence of visual information, motion complexity, and/or active vehicle control [24, 27]. A perception-based cost function allows for implementing these scientific findings on human self-motion perception in a more systematic and extensive way.

9.3.1.4 Optimization Algorithm

The purpose of the optimization algorithm is to find the simulator input commands for which the cost function is minimized within the given constrains. In other words: it finds the allowable simulator input whose percept best approximates the percept in the actual vehicle. For PBMC, several different optimization algorithms can be employed, as long as they are capable of working with constrained nonlinear multi-variable functions.

9.3.1.5 Perception-Based Motion Cueing Framework

By bringing all the elements discussed above together, the PBMC framework is obtained. The flow diagram in Fig. 9.4 provides a simplified illustration of this framework. A vehicle motion is fed to the perception model to compute the vehicle percept, which describes the perception one would have inside the vehicle. The challenge is now to reproduce this same percept in the motion simulator, using appropriate simulator commands. These are calculated using a model of the motion simulator. The simulator motion is passed through the perception model, providing the simulator percept. Note that the perception models computing the simulator and vehicle percept are identical. The cost function provides a quantitative measure of similarity between the two percepts (i.e., the cost), which is used by the optimization algorithm to compute a new set of simulator commands with the aim to decrease the cost. This optimization process is repeated until the cost is reduced below a suitable tolerance level. The optimized simulator commands that result from this

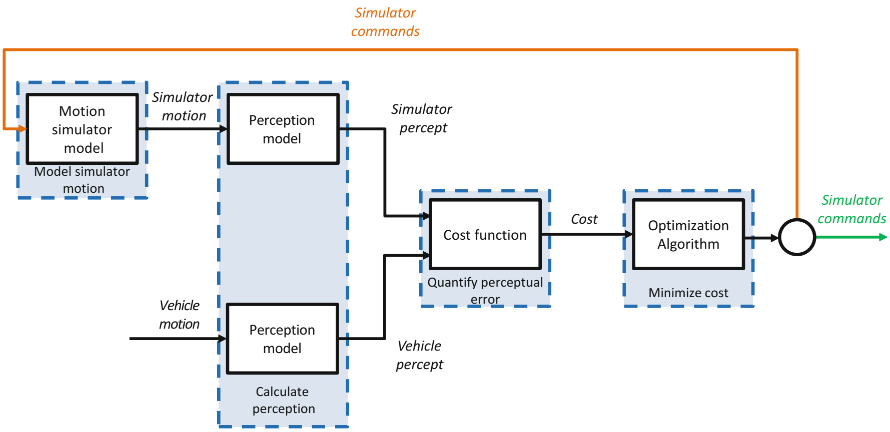

Fig. 9.4 Schematic representation of the PBMC framework. The goal of the PBMC approach is to minimize the cost, i.e., the difference between the simulator percept and the vehicle percept. The optimization of the simulator commands is done iteratively by an optimization algorithm until the optimized simulator commands are obtained

optimization are fed to the actual simulator. Given that models are accurate, the cost function is well-defined and the optimization algorithm successfully minimizes the cost, it is guaranteed that the optimized simulator commands provide a simulator percept that best approximates the vehicle percept.

9.3.2 Applications, Benefits and Limitations

Perception-based motion cueing can increase the realism of motion simulation mainly because the algorithm has more information available than most alternative algorithms. This additional information largely resides in the perception model – providing information on how vestibular and visual stimuli are perceived and integrated into a percept of motion – and the simulator model – providing information on the state and constraints of the simulator.

The perception model allows for exploiting the limitations and ambiguities of human perception. For example, as described in Sect. 9.2.1, under certain circumstances linear acceleration and static tilt are indistinguishable from each other. A perception model, combined with a perception-based cost function, is able to identify and make use of these circumstances. Although this "perceptual trick" appears in many traditional MCA implementations, PBMC does not require the typical tuning and is capable of dynamically adapting the tilt-translation ratio over the course of the simulation. Another example is the exploitation of absolute and differential perceptual thresholds: the human sensory system can only perceive motion stimuli of certain intensity. Stimuli smaller than this absolute threshold are not perceived. Similarly, the human sensory system can only distinguish stimuli when the difference between them is larger than a certain differential threshold. Both types of threshold values depend on many different factors (e.g., motion direction, frequency, intensity, etc.). These factors vary over time, and thus so do the threshold values. By implementing knowledge on these varying thresholds, PBMC is able to determine which motions can and cannot be perceived and which motions can and cannot be distinguished.

The simulator model allows for making more optimal use of the simulator's available workspace. Using the simulator model, PBMC explicitly accounts for actuator limits, exploiting therefore the full spectrum of simulator capabilities. Unlike traditional approaches, PBMC does not scale down the physical motion so that even the most aggressive part of a maneuver still fits within the simulator's workspace. Instead, PBMC processes unscaled physical motion and finds, by means of a perception-based cost function, the simulator inputs that result in the best available cueing, based on the simulator's capabilities. PBMC provides cueing that approaches, but never actually reaches, the actuator limits, making optimal use of the available hardware.

The inclusion of a simulator model makes PBMC also useful in studying simulator concepts themselves. For example, PBMC can be employed in cost-benefit analyses for simulator upgrades, such as the addition of a new axis or the improvement of an existing one. Similarly, it can provide important insight into the development of a simulator concept that does not (yet) exist. PBMC automatically provides the optimal cueing without a dependency on parameters such as the washout filter gains and filter frequencies and is therefore better suited than many traditional methods for the above mentioned scenarios.

The main disadvantage of the PBMC over CMCA is the relative complexity of the algorithm, which inevitably impacts on the speed at which the algorithm operates. At the time of writing, real-time simulations have not yet been achieved. Hence, all tests with PBMC have been performed on pre-recorded maneuvers and offline execution of the PBMC algorithm. For many applications, online calculation operating in real-time are required. In order to achieve this, the current implementation of the PBMC algorithm needs to be further optimized for speed performance. Another drawback that derives from the relative complexity of PBMC is the increased effort to implement a PBMC algorithm. However, this is of less concern, as it can be largely addressed through the development of user-friendly interface solutions. Another disadvantage of the PBMC algorithm here presented is that, in the attempt to bring target and simulator percept as close as possible to each other, it will inevitably favor an inhomogeneous scaling of the trajectory over its time evolution. For instance, in the cueing of a maneuver consisting of two consecutive decelerations, where the first deceleration is twice as strong as the second, the 2:1 proportionality is easily lost if the first deceleration cannot be faithfully reproduced by the simulator. In contrast, in a traditional MCA, a scaling factor is tuned for the entire maneuver to ensure that it fits into the simulator capabilities, and proportionality is therefore more likely maintained.

9.4 Validation of the Perception-Based Motion Cueing Approach

The PBMC approach here introduced would be little more than a conceptually interesting idea, with little lasting impact or practical application, if it would remain without a rigorous and objective evaluation. The goal of such an evaluation is to show the potential benefits and improvements with respect to the current motion cueing approaches. In order to make this comparison possible, a novel methodology was developed, based on psychophysical methods that are typical of human perception research.

9.4.1 The Choice of a Suitable Method

Evaluating the quality of perceived motion is a very complex task, requiring a subjective judgment that can be affected by several factors, like the sensitivity of different sensory modalities, memory, personal preferences, experience and familiarity with the judgment task. Therefore, it is common practice to evaluate the quality of motion cueing by using questionnaires and experts' interviews (which can be executed in more or less rigorous fashion), accompanied by various types of rating scales. Oft-used rating scales are the Visual Analog Scale (VAS) [38], where the response is specified by indicating a position on a continuous line between two end-points, and the Likert-type rating scales [16], where the response is specified by choosing a judgment from a symmetric agree-disagree scale for a series of statements (typically 5, 7, or 9 statements, ranging from completely negative to completely positive judgment). However, both questionnaires and rating scales have several disadvantages that could affect the experimental validation of motion cueing approaches.

Questionnaires and interviews with experts allow for a large degree of freedom in the response, providing typically only qualitative indications. As a result, verbal reports are not a systematic, repeatable and reliable measure of subjective judgments, and should be used only in exploratory studies. Rating scales, on the other hand, provide quantitative numerical estimates and can refer to subtle dimensions or aspects that contribute to the overall judgment. These methods are therefore better suitable for more rigorous statistical analysis. However, also rating scales have features that are disadvantageous for our current purposes, notably the resolution of the Likert-type scale, the presence of scale boundaries and the challenge of qualifying the numerical results with meaningful verbal descriptors. Likert scales have the disadvantage of low resolution (only a few possible responses), which also lead respondents to quickly reach the scale boundaries (once the maximum or minimum rating is given, there is no possibility to assign even higher or lower ratings). It is a general weakness of discrete rating systems that two trials perceived as different could, due to the lack of rating options, be assigned to the same verbal descriptor. This may result in insufficient sensitivity for measuring the multifaceted quality of motion cueing. The VASs, thanks to their analogue nature overcome this limitation of the Likert scales. Nevertheless, it remains difficult to determine appropriate verbal descriptors for the subjective responses along the scale and to quantify their relative distances, as they might not be linearly paced. This limitation becomes even more evident considering that the subjective interpretation of verbal labels may differ among individuals and cultures. In general, rating scales suffer from the limitation of collecting subjective responses that are at best on an ordinal scale, and providing data that are treated as on an interval/ratio scale [10].

These considerations motivated a search for an alternative method providing the following features: (i) sufficient sensitivity to distinguish among subtle differences in the perceive quality; (ii) accounting for subjective differences in the meaning of verbal and numerical labels; (iii) providing numerical quantification on a ratio scale, which allows for traditional statistical analysis and (iv) providing unambiguous interpretation of distances between the judgment scores. We found that the method of *magnitude estimation* with *cross-modality matching* paradigm was suitable for our purposes. This method was originally introduced by Stevens to measure the perceived magnitude of physical intensities [34]. Later the same method was successfully adopted to investigate perceptual aspects of non-physical dimensions, like political opinions [17, 18], aesthetic preferences [12] and linguistic judgments [3]. To the best of our knowledge, the study described here utilizes the magnitude estimation method in the field of motion perception and simulation research for the first time. With this method it is possible to express a judgment about certain features of a stimulus, providing an estimate in any response modality. At the foundations of this method lie the following two assumptions: firstly, the human observer constructs an abstract internal representation of the stimulus' features, which is independent of the sensory modality used to retrieve this representation. Secondly, the observer implicitly attributes a magnitude to the stimulus features that can be expressed on a ratio scale [34]. In an actual experiment, these assumptions allow an observer to produce the quality judgments in any response modality, based on the relative difference in the magnitude of the examined feature over multiple trials. In the study presented here, two response modalities were used to express the magnitude of perceived quality of motion cueing: numerical estimate and line production. Producing a numerical estimate consists of providing a number; while hand-drawing a horizontal line constitutes a line production task. Using magnitude estimates from two response modalities enables 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 the cross-modality matching as a subjective assessment technique, the reader is referred to [26]. The method was used for different purposes throughout the different experimental phases, as described in the experimental procedure below.

9.4.2 Validation Experiment

The following MCAs were tested and compared over three car maneuvers:

- *Classic (CLA)*: classic washout algorithm (cf. Fig. 9.2) using the same filter parameters for all maneuvers
- *Classic Tuned (CLT)*: classic washout algorithm, using filter parameters specifically tuned for each maneuver to better exploit the motion envelope of the simulator
- *Non-weighted Perception-Based (NPB)*: perception-based algorithm using a non-weighted sum of linear accelerations and angular rotations in the cost-function of the optimization algorithm
- *Weighted Perception-Based (WPB)*: perception-based algorithm, similar to the previous one, but with a weighted sum of linear accelerations and angular rotations in the cost function

Eight participants (average age: 29.3 years, 1 female) were recruited through the participants' database of the Max Planck Institute for Biological Cybernetics. They 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 their inclusion. The study was conducted in accordance to the Declaration of Helsinki (1964).

9.4.2.1 Experimental Procedure

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

In the *calibration* phase, participants were familiarized with the magnitude estimation method and the cross-modality matching task. They were asked to assign numerical estimates to different lines of varying lengths and to draw lines whose length was proportional to numbers of varying magnitude. This procedure ensured that participants were able to produce consistent magnitude estimates ($R > .95$) across different response modalities before the actual experiment.

In the *experiment* phase, participants were accommodated inside the CyberMotion Simulator (CMS) and exposed to motion trajectories (Fig. 9.5). The CMS is a dynamic simulator that was developed to expand the limited workspace and dexterity of traditional hexapod-based simulators [25]. It is an 8-degrees-of-freedom serial robot, where a 6-axes industrial robot manipulator is mounted on a linear rail and equipped with a motorized cabin at the end effector (Fig. 9.5, left). The cabin is equipped with two 1920×1200 projectors (Eyevis, Germany) and interference filter stereo projection system (Infitec GmbH, Germany), which provide up to 160×90 deg Field-of-View on the cabin inner side (Fig. 9.5, right). The cabin is also equipped with mounting possibilities for haptic control devices used for flight and driving simulation, as well as for head motion and gaze tracking.

The motion trajectories consisted of synchronized video, inertial and audio recordings of a car performing three maneuvers: strong braking, going around a roundabout and slalom. Inertial data were obtained from an inertial navigation system, while the video was captured with two full-HD cameras positioned near the driver's head in the actual car [37]. The use of recorded trajectories ensured that participants were exposed to the same motion stimuli and immersed in a realistic multi-sensory (visual, auditory and inertial) simulation. This also allowed the use of 3D video projection to further enhance the simulation realism. During the trajectory playback, two superimposed auditory signals (beeps) indicated the beginning and the end of each maneuver.

Participants were instructed to pay attention to the motion information ("*what you feel*") in between these two beeps and how it relates to the visual information ("*what you see*"). After every trajectory playback, they were required to draw a horizontal line and provide a numerical estimate. These had to be proportional to either their impression of the motion aspect that was asked for. They were asked about the following aspects[1]:

[1] For brevity, the first aspect is later referred to as "motion direction", and the second as "motion strength".

Fig. 9.5 The MPI CyberMotion Simulator. Exteriors (*left*) and cabin interiors (*right*)

- *"Agreement of motion direction: how well does the direction of the motion you feel agree with the direction of the motion you see?"* High level of agreement between the visual and inertial motion directions would result in long lines and large numbers, low level of agreement would result in shorter lines and smaller numbers.
- *"Appropriateness of motion strength: How appropriate is the strength of the motion you feel compared to the motion you see?"* Appropriate motion strength (neither too strong nor too weak) would result in long lines and large numbers, inappropriate motion strength would result in shorter lines and smaller numbers.

The questions appeared on the screen, while the simulator was steady in an upright position. The participants were instructed to provide any line length/positive number for the first answer, keeping in mind that they might want to provide longer/shorter lines and larger/smaller numbers later on. The two questions were assessed on separate blocks of trials, with the order of the questions balanced across participants. Each of the three maneuvers was reproduced with four different MCAs, for a total of 12 trajectories per block. The order of the maneuvers and the order of MCAs per maneuver were randomized across participants. A different maneuver (double lane change) was used as training before each block to familiarize the participants with the questions, the response procedure, the different MCAs and the simulation environment.

As additional data, the following information was recorded: motion sickness questionnaires were collected for all participants before and after the experiment phase [15]. During the experiment, the level of sickness was monitored every 10 min using a numerical score [9]. After the experiment, participants filled out a questionnaire to report their subjective ratings about mental demand, level of concentration, ability to maintain a constant level of attention, level of frustration and physical comfort on a 9-point rating scale.

In the *verbal qualification* phase, participants were asked to evaluate the perceived magnitude of a set of verbal qualifiers [32] indicating "quality" (e.g., "good", "bad", "so-so") using the same method of the previous phases, i.e. magnitude estimation task with cross modality matching (numerical estimate and line production). This allows for a verbal interpretation of the numerical results of the MCAs quality ratings, and provides an indication of the subjective distance between verbal qualifiers.

Overall, the evaluation experiment lasted about 2.5 h and was structured as follows:

- Calibration task: magnitude estimation of lines and numbers
- Baseline questionnaire about motion sickness
- Training on the first question (i.e., strength or direction, 4 trials)
- First experiment block: 12 trials
- Verbal qualifiers: magnitude estimation of verbal qualifiers
- 15 min break
- Training on the second question (i.e., strength or direction, 4 trials)
- Second experiment block: 12 trials
- Verbal qualifiers: magnitude estimation of verbal qualifiers
- Post experiment questionnaire about motion sickness

9.4.2.2 Data Analysis and Results

One participant did not complete the experiment due to mild symptoms of motion sickness and was therefore excluded from the analysis. The remaining seven participants showed a high correlation ($R > .95$) between numerical estimates and lines length in the calibration phase, and were therefore included in the experiment and in the data analysis. The raw numerical estimates and lines lengths collected in the experiment were normalized and a combined standard score was computed from the mean of the normalized values. A similar procedure was adopted for the analysis of the verbal qualifiers. The results of the motion cueing quality rating are shown in Fig. 9.6, plotted against the verbal descriptors and the overall standard score.

Due to the different characteristics of the tested maneuvers, and the supposed independence of the judgments between the rated motion aspects, considerably different patterns of results were to be expected. Therefore, a repeated-measure analysis of variance (rmANOVA) was run independently for each maneuver (brake, roundabout or slalom) and rated aspect (motion direction or strength) to test the effect of MCAs on the perceived quality of motion cueing. Post-hoc tests with Bonferroni correction for multiple comparisons were used. The significant results are reported in Table 9.1.

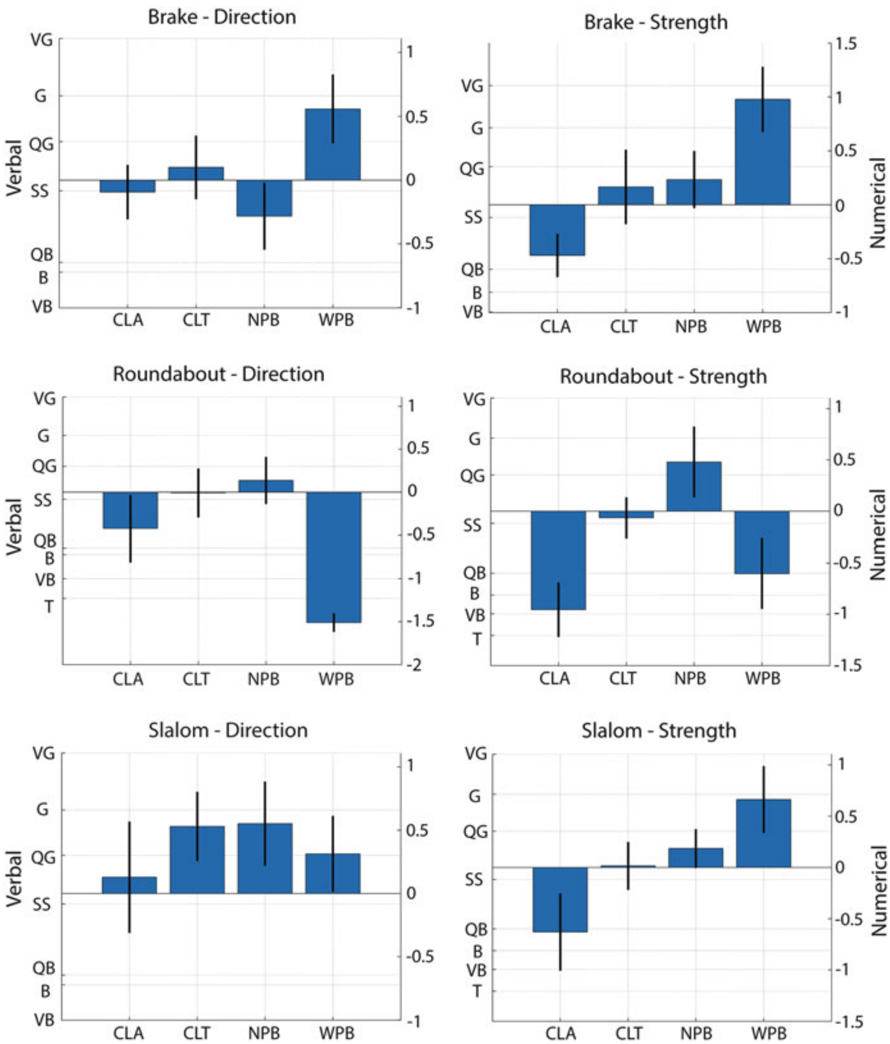

Fig. 9.6 Averaged standard score across subjects of the quality ratings of PBMC (3rd and 4th bar of each plot), as compared to CMCA (1st and 2nd bar of each plot). The *lines* indicate standard error. Each plot refers to one of the maneuvers (brake, roundabout or slalom) and rated aspect (motion direction or strength). Verbal qualifiers are indicated on the left vertical axis: *VG* very good, *G* good, *QG* quite good, *SS* so-so, *QB* quite bad, *B* bad, *VB* very bad, *T* terrible

The PBMC algorithm was rated as good as the CMCA or better in all conditions, except for the roundabout. With regards to the appropriateness of motion strength, the results show a clear preference for either version of the PBMC in all the tested maneuvers. In terms of motion direction, i.e. the level of agreement between the direction of inertial motion as compared to the direction of the visual motion, the performance of the perception-based approach is comparable to the filter-based approach in the brake and the slalom maneuvers; while it is lower in the roundabout.

Table 9.1 Significant results of rmANOVA and post-hoc tests

rmANOVA (maneuver, motion aspect)	Post-hoc tests
$F(3,28) = 4.38$, $p < 0.05$(brake, motion strength)	WPB > CLA
$F(3,28) = 6.97$, $p < 0.01$(roundabout, motion direction)	CLT > WPBNPB > WPB
$F(3,28) = 4.54$, $p < 0.05$(roundabout, motion strength)	NPB > CLA
$F(3,28) = 3.38$, $p < 0.05$(slalom, motion strength)	WPB > CLA

Nevertheless, in the roundabout maneuver the NPB algorithm receives similar quality ratings as the classic algorithms.

Overall, the results of this first validation experiment are encouraging, as they indicate that, already in its first implementation, the perception-based solution is positively rated. Moreover, the results show that the methodology chosen for the experiment is appropriate for the collection of quantitative data and the use of inferential statistics, which can be used to find differences on the quality score of MCAs.

9.5 Conclusions and Future Development

The first experimental validation of the PBMC approach described here has shown that an improvement in the current standards of motion cueing algorithms is possible. Remarkably, this approach shows great potential for future applications, as it can provide advantages to both simulator users and engineers. The quality of a classical MCA depends strongly on the tuning. Tuning is expensive and can only be done by experts. By reducing the amount of tuning required, simulator users can increase the quality of their simulation while reducing costs. Finally, the classical approach does not make optimal use of the simulator capabilities. By improving the way the MCA exploits the hardware, simulator users increase their return on investment.

As suggested by the data collected in the roundabout maneuver, more work is needed to further investigate the relation between measured overall quality and the weights given to each motion cue in the perceptual cost function. Therefore, more knowledge is needed on the relation between the measured quality of motion cueing algorithms and the quality as assumed by the optimization algorithms. With this regard, the difficulty of measuring subjective experience and preferences remains a main challenge. To gain a better understanding of this relation it is essential to know how this measured MCA quality evolves over time. Further research is ongoing to include in the evaluation methodology also continuous measurement of perceived coherence between visual and actual motion in the simulation. Due to its modular structure, PBMC will also directly benefit from advances in self-motion perception modelling, an active and dynamic research field. Among the open questions, individual differences between humans and the role of sensory and cognitive factors typical of everyday scenarios are certainly of great relevance for further development of PBMC. By continuing in its quest of filling the gap between what is known about human self-motion perception and what is used in motion simulation, PBMC will allow for increasingly relevant improvement of the quality, realism and usefulness of motion simulations.

Acknowledgments The research described in this publication was funded by the German Federal Ministry of Education and Research under grant number 03V0138. The responsibility for the contents of this publication lies with the author. This study was supported by the Max Planck Society, by the WCU (World Class University) program and by the Brain Korea 21 PLUS Program both funded by the Ministry of Education through the National Research Foundation of Korea.

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