Summary

Motion-based vehicle simulators are frequently used in research and development, e.g., for human factors evaluations and vehicle design, as well as for pilot/driver training, as such simulations provide a safe and cost-effective testing environment. Visual and physical motion cues are combined to provide occupants with a feeling of being in the real vehicle. While visual cues are generally not limited in amplitude, physical cues certainly are, due to the limited simulator motion space. A motion cueing algorithm (MCA) is used to map the vehicle motions onto the simulator motion space. This mapping inherently creates mismatches between the visual and physical motion cues.

Due to imperfections in the human perceptual system, not all visual/physical cueing mismatches are perceived. However, if a mismatch is perceived, it can impair the simulation realism and even cause simulator sickness. For MCA design, a good understanding of *when* mismatches are perceived, and ways to *prevent* these from occurring, are therefore essential. While most other research tries to predict perceived mismatches based on complex non-linear models of human perception, in this thesis a data-driven approach, using continuous subjective measures of Perceived Motion Incongruence (PMI), is adopted. PMI refers to the effect that perceived mismatches between visual and physical motion cues have on the resulting simulator realism. When a mismatch is perceived, but does not influence the simulation realism, the PMI is low, while a mismatch that is detrimental to simulator realism results in a high PMI. In this thesis we focus on car driving, but the proposed methods can also be applied to other vehicles.

One often-occurring type of mismatch between visual and physical motion cues is referred to as scaling errors. Such errors are caused by a pure (down) scaling of the vehicle physical motion, such that it fits in the simulator motion space. MCAs also make use of tilt-coordination, where the gravitational force and a non-zero rotation with a rotational rate below human perception threshold, are used to simulate sustained accelerations. This mechanism can cause shape differences between the visual and physical motion signals, resulting in other types of cueing errors, i.e., missing or false cues. It is well known that missing or false cues are more likely to be perceived than scaling errors with a similar amplitude and are often more detrimental to simulator realism. Thus, not only the magnitude of the mismatch, but also the *type of mismatch* is important information when designing and optimizing an MCA. While this is widely accepted knowledge and is implicitly used by experts to tune MCAs, currently this knowledge is not explicitly used in MCA optimization due to its qualitative, rather than quantitative, nature.

Another characteristic of simulator realism is that it is inherently *time-varying*. While a simulation might feel mostly realistic, momentary manoeuvres requiring a large motion space, such as driving a roundabout, can cause a sudden decrease in realism. Currently, experts often apply worst-case MCA tuning, resulting in suboptimal physical motions for those parts of the simulation that do not require this large motion space. Certain MCAs, such as those based on model predictive control, on the other hand, can optimize the simulator realism at each simulation time step. This thesis aims to connect the benefits of expert knowledge on motion cue mismatches with the advantage of optimization algorithms in dealing with the time-varying aspect of simulation realism. It aims to develop an MCA-independent, offline prediction method for time-varying PMI during vehicle motion simulation, with the purpose of improving motion cueing quality. To this end, the thesis is divided in three parts, dedicated to *measuring*, *modelling* and *minimizing* PMI, respectively.

Part I focuses on the development of a novel method to *measure* time-varying PMI using a continuous subjective rating. Two human-in-the-loop experiments were performed, where participants were asked to rate the PMI continuously throughout several repetitions of a passive driving simulation. The first experiment, Experiment 1, assessed the reliability and validity of the method itself. Comparing the ratings of several repetitions of the same simulation showed consistency in participants' ratings, verifying the reliability of the method. The validity of the method was assessed by comparing the continuous ratings to a more established time-independent rating method and to expert knowledge from literature on the different cueing error types. The continuous ratings correlated well with a time-independent rating method for each segment of the simulation and was also consistent with expert knowledge on the relative PMI between several scaled, missing and false cues.
In a second experiment, Experiment 2, the continuous rating method was applied to compare the performance of two motion cueing algorithms in a highly realistic vehicle motion simulation. Again, participants were able to provide consistent continuous ratings across several repetitions of the same simulation and their time-independent ratings for each tested MCA setting compared well to their average continuous rating. This confirmed the reliability and validity of the continuous rating method, also for more realistic vehicle simulations.

In **Part II**, the data obtained with the two experiments described in Part I were used to develop PMI *models*, to predict the time-varying PMI within and between experiments. A general model structure was designed to map visual and physical motion cues onto a Motion Incongruence Rating (MIR), which represents the time-varying rating of PMI obtained with the continuous rating method. First, the model translates the visual and physical cues into different types of cueing errors that are combined into one measure of PMI and then filtered to obtain the modelled Motion Incongruence Rating (MIR). A wavelet-based Cueing Error Detection Algorithm (CEDA) was developed to differentiate between scaled, missing and false cues, and its parameters were tuned using data from Experiment 1. Applying the algorithm showed that the CEDA could distinguish between scaled, missing and false cues as hypothesized.
To determine within-experiment prediction capabilities, three models of different complexity were derived from the general model template. These models were fitted to the first half of the data from Experiment 1, after which their prediction power was assessed using the second half of this dataset. The prediction results showed that all models could predict important PMI features and that the prediction improved with increasing model complexity. An interesting observation was also that false cues were modelled as being two times more detrimental than scaled cues for the same cueing error magnitudes. Overall it was shown that the models can indeed link different type of cueing errors to decreases in cueing quality and predict such decreases for data within one experiment.
To compare datasets from different experiments, first a method for estimating a Model

Transfer Parameter (MTP) was developed, with which ratings from one experiment can be mapped onto the ratings of a second experiment. The MTP needed to align the ratings from Experiment 1 and 2 was estimated with this method and used to assess the between-experiment prediction capabilities of the three derived models. Good prediction capabilities were obtained only when a rich enough dataset was used for model fitting. The hypothesis that better models can be obtained when increasing the richness of the estimation dataset was supported by the fact that models fitted to aggregated data from both experiments were more accurately matched to the measured ratings then those fitted to either dataset.

Part III focuses on *minimizing* PMI. The capabilities of the PMI models in predicting decreased cueing quality opens up opportunities to improve this quality. The predictions can, for example, be used to tune MCAs such that the most critical drops in cueing quality are avoided. Additionally, developing these PMI models, by correlating the time-varying PMI to different cueing errors, can help in gaining a better understanding of what exactly causes decreased cueing quality. In this thesis, a PMI model was used in an optimization-based MCA. The weights for linear acceleration and rotational velocity visual-physical cues differences in the cost function of this MCA were estimated using a static version of the least complex PMI model from Part II and data from both Experiments 1 and 2.
In a third human-in-the-loop experiment, Experiment 3, the cueing quality of the MCA with the PMI model weights was compared to the cueing quality of the MCA with its original weights, which accounted solely for the differences in unit between linear acceleration and rotational velocity. The results showed that only a small group of participants, all with prior simulator experience, preferred the MCA with the PMI model weights. The preference of the remaining, larger group seemed to mainly be based on a preference for "lower than unity gains" between vehicle and simulator motions, which is consistent with earlier literature, but was not yet accounted for in the PMI models. Overall, the results indicate that for MCA optimization a PMI model needs to be fitted to a much richer dataset in terms of, among others, number and variety of participants, cueing errors and simulators.

In this thesis a novel approach to improve perceived cueing quality of motion cueing algorithms was introduced. A complete roadmap, describing how to *measure* and *model* PMI and how to apply such models to predict and *minimize* PMI in motion simulations was presented. The results presented in this thesis show the potential of this novel approach. For future research it is recommended to adapt the developed PMI measurement method for use in active driving simulations and improve the PMI models by designing algorithms to detect additional cueing error types. It is also recommended to gather more and richer PMI rating data via human-in-the-loop experiments to improve the parameter estimation of these models. Finally, a systematic investigation on how and under which circumstances these models can be used to improve cueing quality should also be performed. With these advances, the approach outlined in this thesis can enable major improvements in simulator cueing and realism.

Samenvatting

Bewegingssimulatoren worden vaak gebruikt in onderzoek en ontwikkeling, voor bijvoorbeeld de evaluatie van menselijke factoren en het ontwerp van voertuigen, alsook voor de opleiding van piloten/bestuurders, omdat dergelijke simulatoren een veilige en kosteneffectieve testomgeving bieden. Visuele en fysieke bewegingsstimuli worden gecombineerd om de inzittenden het gevoel te geven dat ze zich in het echte voertuig bevinden. Alhoewel visuele bewegingsstimuli over het algemeen niet beperkt zijn in amplitude, zijn fysieke bewegingsstimuli dat zeker wel, vanwege de beperkte bewegingsruimte van de simulator. Een bewegingsalgoritme, een zogenaamd 'Motion Cueing Algorithm (MCA)', wordt gebruikt om de bewegingen van het voertuig te projecteren op de bewegingsruimte van de simulator. Deze projectie creëert van nature discrepanties tussen de visuele en inertiële bewegingsstimuli.

Door onvolkomenheden in het menselijke perceptuele systeem worden niet alle visuele/inertiële bewegingsstimuli discrepanties waargenomen. Als een discrepantie echter wél wordt waargenomen, kan dit het ervaren realisme van de simulatie aantasten en zelfs simulatieziekte veroorzaken. Voor het ontwerpen van MCAs is een goed begrip van *wanneer* discrepanties worden waargenomen en hoe deze kunnen worden *voorkomen*, daarom essentieel. Terwijl de meeste andere onderzoeken proberen om waarneembare discrepanties te voorspellen op basis van uitgebreide niet-lineaire modellen van menselijke perceptie, wordt in dit proefschrift een datagestuurde benadering toegepast, gebruikmakend van continue subjectieve metingen van de waargenomen bewegingsincongruentie (PMI). PMI verwijst naar het effect dat waarneembare discrepanties tussen visuele en inertiële bewegingsstimuli hebben op het resulterende realisme van de simulator. Wanneer een discrepantie wordt waargenomen, maar niet als erg storend ervaren wordt in het simulatierealisme, is de PMI laag, terwijl een discrepantie die schadelijk is voor het simulatorrealisme resulteert in een hoge PMI. In dit proefschrift richten we ons op het autorijden, maar de voorgestelde methoden kunnen ook worden toegepast op simulaties van andere voertuigen.

Een vaak voorkomende vorm van discrepantie tussen visuele en inertiële bewegingsstimuli zijn schalingsfouten. Dergelijke fouten worden veroorzaakt door een pure (terug) schaling van de fysieke beweging van het voertuig, zodat deze in de bewegingsruimte van de simulator past. Om aanhoudende versnellingen te simuleren, maken MCAs gebruik van "tilt-coordination", i.e., het langzaam kantelen van de simulator. Hierbij kantelt de simulator met een rotatiesnelheid onder de menselijke waarnemingsdrempel, zodat een component van de zwaartekracht leidt tot een ervaren versnelling van het lichaam. Dit mechanisme kan vormverschillen veroorzaken tussen de visuele en inertiële bewegingssignalen, wat resulteert in andere soorten fouten, zoals ontbrekende of foutieve signalen. Het is bekend dat ontbrekende of foutieve signalen eerder worden waargenomen dan schalingsfouten met een vergelijkbare amplitude en dat ze vaak schadelijker zijn voor het ervaren realisme van de simulator. Daarom geeft dus niet alleen de grootte van de discrepantie, maar ook het type van de discrepantie belangrijke informatie voor het ontwerpen en optimaliseren van een MCA. Hoewel dit algemeen aanvaarde kennis is en impliciet door experts wordt gebruikt om MCAs af te stemmen, wordt deze kennis momenteel niet expliciet gebruikt in MCA-optimalisatie

vanwege het veelal kwalitatieve, in plaats van voor optimalisatie vereiste kwantitatieve, karakter ervan.
Een ander kenmerk van simulatorrealisme is dat het van nature varieert over tijd. Ook als een simulatie voor het merendeel van de tijd realistisch aanvoelt, kunnen kortstondige manoeuvres die een grote bewegingsruimte vereisen, zoals het rijden over een rotonde, een plotselinge daling van het realisme veroorzaken. Op dit moment stemmen experts de MCAs vaak af zodat de projectie van de grootste bewegingsamplitudes in de bewegingsruimte past, wat resulteert in suboptimale inertiële bewegingen voor die delen van de simulatie die deze grote bewegingsruimte helemaal niet nodig hebben. Bepaalde MCAs, zoals die op basis van "Model Predictive Control", kunnen daarentegen het realisme van de simulator bij elke stap in de simulatie optimaliseren.
Dit proefschrift streeft ernaar de voordelen van deskundige kennis over de discrepanties tussen visuele en fysieke beweginsstimuli te combineren met het voordeel van deze moderne optimalisatiealgoritmes in het omgaan met het tijdsveranderende aspect van het simulatierealisme. Het doel is om een MCA-onafhankelijke, offline methode te ontwikkelen om de tijdsafhankelijke PMI tijdens de simulatie van voertuigbewegingen te voorspellen, met de intentie de kwaliteit van de bewegingssimulatie van het voertuig vervolgens te verbeteren. Hiertoe is het proefschrift opgedeeld in drie delen, respectievelijk gewijd aan het *meten*, *modelleren* en *minimaliseren* van PMI.

Deel I richt zich op de ontwikkeling van een nieuwe methode voor het *meten* van de tijdveranderende PMI, die gebruik maakt van een continue subjectieve waardering. Er werden twee mens-in-de-loop experimenten uitgevoerd, waarbij de deelnemers werd gevraagd de PMI continu te waarderen gedurende verschillende herhalingen van een passieve rijsimulatie.
Het eerste experiment, Experiment 1, beoordeelde de betrouwbaarheid en validiteit van de methode zelf. Het vergelijken van de waarderingen van verschillende herhalingen van dezelfde simulatie toonde consistentie in de waarderingen van de deelnemers en verifieerde de betrouwbaarheid van de methode. De validiteit van de methode werd geanalyseerd door de continue beoordelingen te vergelijken met een meer gevestigde tijdsonafhankelijke beoordelingsmethode en met de kennis van deskundigen uit de literatuur over de verschillende typen bewegingsstimuli fouten. De continue waarderingen correleerden goed met een tijdonafhankelijke waarderingsmethode voor elk segment van de simulatie en waren ook consistent met de kennis van de relatieve PMI tussen verschillende geschaalde, ontbrekende en foutieve bewegingsstimuli.
In een tweede experiment, Experiment 2, werd de continue waarderingsmethode toegepast om de prestaties van twee MCAs in een zeer realistische bewegingssimulatie van het voertuig te vergelijken. Opnieuw waren de deelnemers in staat om consistente continue waarderingen over meerdere herhalingen van dezelfde simulatie te geven en waren hun tijdonafhankelijke waarderingen voor elk geteste MCA goed te vergelijken met hun gemiddelde continue waarderingen. Dit bevestigde de betrouwbaarheid en validiteit van de continue waarderingsmethode, ook voor meer realistische voertuigsimulaties.

In **Deel II** werden de gegevens verkregen met de twee experimenten beschreven in Deel I, gebruikt voor de ontwikkeling van PMI *modellen*, om de tijd variërende PMI in en tussen experimenten te voorspellen. Een algemene modelstructuur werd ontworpen om visuele en inertiële bewegingsstimuli te vertalen naar een bewegingsincongruentie

waardering, de Motion Incongruence Rating (MIR). De MIR vertegenwoordigt de tijd-variërende waardering van PMI, verkregen met de continue waarderingsmethode. Eerst vertaalt het model de visuele en inertiële bewegingsstimuli in verschillende typen discrepanties die gecombineerd worden in één maat van PMI en vervolgens gefilterd worden om de gemodelleerde MIR te verkrijgen. Een op wavelet-gebaseerde bewegingsstimuli discrepantie detectie algoritme (CEDA) werd ontwikkeld om onderscheid te maken tussen geschaalde, ontbrekende en foutieve bewegingsstimuli, waarbij de parameters werden geschat met behulp van gegevens van Experiment 1. Het toepassen van het algoritme toonde aan dat de CEDA onderscheid kon maken tussen geschaalde, ontbrekende en foutieve bewegingsstimuli zoals verondersteld.
Om de intra-experiment voorspellingscapaciteiten te bepalen, werden drie modellen van verschillende complexiteit afgeleid van de algemene modelstruktuur. De eerste helft van de gegevens van Experiment 1 is gebruikt voor de parameter schatting van de drie modellen, waarna hun voorspellend vermogen is geanalyseerd met behulp van de tweede helft van deze dataset. De voorspellingsresultaten toonden aan dat alle modellen belangrijke PMI-kenmerken konden voorspellen. De voorspelling verbeterde met de toenemende complexiteit van het model. Een interessante observatie was ook dat foutieve bewegingsstimuli werden gemodelleerd als twee keer schadelijker dan geschaalde bewegingsstimuli voor dezelfde bewegingsstimuli discrepantie magnitudes. In het algemeen werd aangetoond dat de modellen inderdaad verschillende soorten bewegingsstimuli fouten kunnen koppelen aan de gemeten dalingen in bewegingsstimuli kwaliteit en dat dergelijke dalingen te voorspellen zijn voor data binnen één experiment.
Om datasets uit verschillende experimenten te vergelijken, werd eerst een methode ontwikkeld voor het schatten van een Model Transfer Parameter (MTP), waarmee de waarderingen van het ene experiment kunnen worden geprojecteerd op de waarderingen van een tweede experiment. De MTP die nodig was om de waarderingen van Experimenten 1 en 2 te vergelijken werd geschat met deze methode en gebruikt om het voorspellende inter-experiment vermogen van de drie afgeleide modellen te analyseren. Goede voorspellingsmogelijkheden werden alleen verkregen wanneer er een voldoende rijke dataset werd gebruikt voor de parameter schatting. De hypothese dat betere modellen kunnen worden verkregen naarmate de schattingsdataset rijker is, werd ondersteund door het feit dat de modellen die op geaggregeerde gegevens van beide experimenten werden geschat, de gemeten waarderingen beter volgden dan de modellen die op een van beide datasets werden geschat.

Deel III, richt zich op het *minimaliseren* van de PMI. Het vermogen van de PMI-modellen om een verminderde bewegingsstimuli kwaliteit te kunnen voorspellen biedt mogelijkheden om deze kwaliteit te verbeteren. De voorspellingen kunnen bijvoorbeeld worden gebruikt om de kortstondige bewegingsstimuli kwaliteit zo af te stemmen dat de meest kritische kwaliteitsdalingen worden vermeden. Bovendien kan de ontwikkeling van deze PMI modellen, door het correleren van de tijdveranderende PMI met verschillende bewegingsstimuli fouten, helpen om een beter begrip te krijgen van wat precies de verminderde bewegingsstimuli kwaliteit veroorzaakt.
In dit proefschrift werd een PMI model gebruikt in een op optimalisatie gebaseerd MCA. De gewichten voor de verschillen tussen de visuele en inertiële bewegingsstimuli voor lineaire versnelling en rotatiesnelheid in de kostenfunctie van dit MCA werden geschat met behulp van een statische versie van het minst complexe PMI model van deel II en gegevens van zowel Experimenten 1 en 2.

In een derde mens-in-de-loop experiment, Experiment 3, werd de bewegingsstimuli kwaliteit van het MCA met de op het PMI model gebaseerde gewichten vergeleken met de kwaliteit van het MCA met zijn oorspronkelijke gewichten, die alleen rekening hielden met de verschillen in eenheid tussen lineaire versnelling en rotatiesnelheid. De resultaten toonden aan dat slechts een kleine groep deelnemers, allen met ervaring in de simulator, de voorkeur gaf aan het MCA met de op het PMI model gebaseerde gewichten. De voorkeur van de resterende, grotere groep, leek vooral gebaseerd te zijn op een voorkeur voor 'lager-dan-eenheid-schaling' tussen voertuig- en simulatorbewegingen, wat consistent is met eerdere literatuur, maar nog niet in de PMI modellen is verwerkt. In het algemeen, wijzen de resultaten erop dat voor MCA optimalisering een PMI model op een dataset moet worden geschat die veel rijker is in termen van, onder andere, aantal en verscheidenheid van deelnemers, bewegingsstimuli fouten en simulatoren.

In dit proefschrift werd een nieuwe aanpak geïntroduceerd om de waargenomen bewegingsstimuli kwaliteit van MCAs te verbeteren. Een compleet stappenplan werd gepresenteerd, waarin wordt beschreven hoe PMI te *meten* en te *modelleren* en hoe dergelijke modellen toe te passen om PMI in bewegingssimulaties te voorspellen en te *minimaliseren*. De resultaten die in dit proefschrift worden beschreven, tonen het potentieel van deze nieuwe aanpak.
Voor toekomstig onderzoek wordt aanbevolen om de ontwikkelde PMI meetmethode aan te passen voor gebruik in actieve rijsimulaties en de PMI modellen te verbeteren door algoritmes te ontwerpen om meer types bewegingsstimuli fouten te detecteren. Het wordt verder aanbevolen om meer en rijkere PMI waarderingsdata te verzamelen via mens-in-de-loop experimenten om de parameterschatting van deze modellen te verbeteren. Ten slotte moet ook een systematisch onderzoek worden uitgevoerd naar hoe en onder welke omstandigheden deze modellen kunnen worden gebruikt om de kwaliteit van de bewegingsstimuli te verbeteren. Met deze vooruitgang kan de in dit proefschrift geschetste aanpak belangrijke verbeteringen in simulator bewegingsstimuli realisme mogelijk maken.

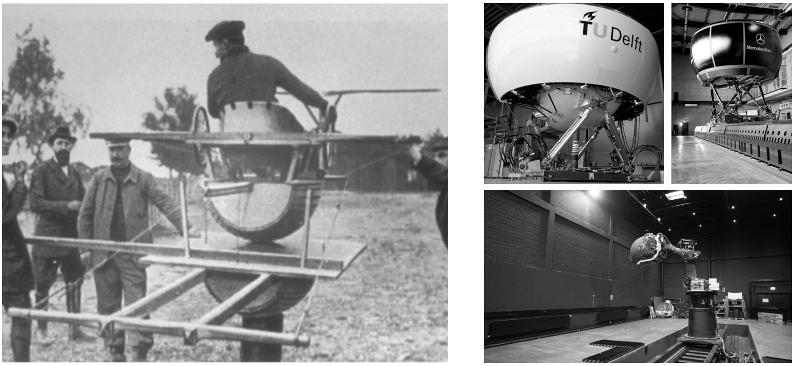
1

Introduction

Humans always wanted to go faster and higher than their own legs could carry them. This led them to invent numerous types of vehicles to move fast over land, water and air. As training how to handle such vehicles and testing new developments can be dangerous and costly, vehicle motion simulators were invented. In 1910 the first vehicle motion simulator, the Antoinette trainer (Figure 1.1(a)), was developed to safely train pilots how to control an aircraft while staying on the ground. Since then, motion simulator technology has evolved tremendously and many different types of motion simulators have been developed for a range of vehicle types (Figure 1.1(b)).

In the aerospace industry, motion simulators have increased flight safety by providing a safe and cost effective way for pilot training, while also reducing the environmental impact as less airborne training is required [1]. Simulators used for pilot training often consist of a Stewart platform [2], or hexapod platform (see Figure 1.1(b) TU Delft simulator), to provide the physical motions cues and a cabin with display to host the pilot and provide visual motion cues. Aircraft manufacturers such as Airbus and Boeing, but also large airlines such as Air France - KLM and Lufthansa, operate several training centers with dozens of full motion flight simulators especially for training purposes. Apart from pilot training, flight simulators are used for aerospace research and development, such as display design [3], handling quality assessment [4, 5] and even accident investigation [6].

In the automotive industry, the focus of this thesis, also increasing use is made of motion simulators. For race car driving physical motion cues during high translational vehicle acceleration are important for proper driver training [7, 8]. Simulator-based eco-driving training for truck and bus drivers can help to decrease fuel consumption [9, 10], while simulator-based investigations into driving behaviour under dangerous conditions can help to improve driver safety [11, 12]. Also during the car design process motion simulators are used for, for example, chassis testing [13], evaluation of steering feel [14] or development of driver assistance systems [15, 16]. Due to the importance of linear motion during car manoeuvres, the motion simulators of big car manufacturers such as Daimler [17], Renault [18], Toyota [19] and soon also BMW [20], consist of a hexapod platform on top of a linear track or X-Y table, to expand the horizontal and lateral motion limits. The cabin is usually large enough to house a real size car and often contains a 360 degrees display.



(a) (b)

Figure 1.1: (a) Antoinette Trainer. (b) current vehicle motion simulators (top left: SIMONA Research Simulator, TU Delft, top right: Daimler Simulator, bottom: CyberMotion Simulator, MPI for Biological Cybernetics).

In the aerospace industry specialized motion simulators have also been developed to simulate specific parts of space flight. The vertical motion simulator at NASA Ames [21], for example, was designed to simulate the vertical take-off and landing of air- and spacecraft. The Desdemona, operated by Desdemona B.V. and AMST, having a centrifuge design motion platform and gimbaled cabin, was initially designed for disorientation training [22].
Other novel simulator designs such as the Cybermotion [23] and CableRobot [24] simulators at the Max Planck Institute for Biological Cybernetics are, for example, used for motion perception research. In the DriverLab at Toronto Rehabilitation center [25] the influence of physical and mental health on driving performance is investigated. This simulator has additional realistic features such as a weather and glare simulator to simulate rain and oncoming headlights.
While new technologies and simulator designs have greatly improved the realism of vehicle motion simulators, generating realistic physical motion cues while staying within the simulator workspace remains one of the grand challenges of vehicle motion simulation. Realistic motion cues are needed for many aspects of transfer of training in aircraft [26, 27]. Transfer of training related to fuel consumption reduction was also greater when providing eco-driving training in motion-base simulators compared to a fixed-base simulator [28]. Motion cueing has also been shown to significantly affect driving behaviour during, for example, braking [29] and curve driving [30, 31]. Especially for driving behaviour research, and vehicle and human support system development which rely on simulating realistic driving behaviour, realistic motion cueing is extremely important. However, while the addition of physical motion cues increases simulation realism [32, 33], poor cueing can actually cause a significant *reduction* in realism and even lead to simulator sickness [34]. In cases of very poor motion cueing no motion is often preferred to motion [27, 35, 36]. Much research is therefore done in improving the realism of physical motion cues, such as taking into account human perception models [37–39], implicitly [40] or explicitly [41, 42] accounting for simulator constraints or accounting for future simulator motions [43, 44] when generating phys-

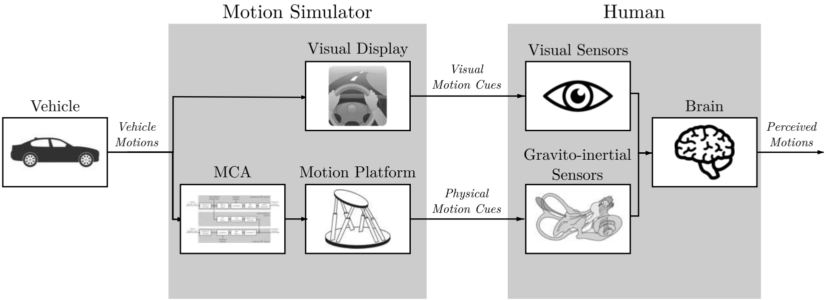


Figure 1.2: General scheme of motion cueing in a vehicle motion simulator.

ical motion cues, or specializing the generation of physical motion cues for specific simulation scenarios [45, 46].

1.1. Motion cueing algorithms

In Figure 1.2 a general scheme for motion cueing in a vehicle simulator is presented. The simulator motions, usually taken as the linear acceleration and rotational velocity, are used unrestricted to generate a visual scene that is displayed inside the motion simulator. From these visuals, visual motion cues are derived and sensed by the human visual system. A parallel path is shown for the physical motion cues, which are presented via the motion platform and sensed by the human gravito-inertial sensors such as the vestibular and somatosensory systems. The motion platform workspace, however, is restricted. Therefore, the vehicle motions are run through a motion cueing algorithm (MCA), which maps the vehicle motions onto the limited simulator workspace, *before* being send to the motion platform. Finally, the sensed visual and physical motion cues are then combined in the human brain and a percept of self motion is obtained.
Most simulators use an MCA that is based on the Classical Washout Filter (CWF) [47]. This MCA uses high pass filters to extract the high-frequency content of the linear accelerations and rotational velocities and sends only those to the simulator motion system. Low-pass filters are used to extract the low-frequency content of the lateral and longitudinal accelerations for what is called "tilt-coordination" [48], i.e., rotating instead of translating the cabin to simulate prolonged accelerations. If the rotations occur at a rate below the human perceptual thresholds, the physical rotation angle and the visual cues for linear acceleration combined are perceived as sustained acceleration rather than rotation [49]. To avoid the simulator hitting its limits, worst-case tuning of the MCA parameters is usually applied [50]. This type of tuning involves scaling down all motions, i.e., global scaling, such that those parts of the simulation that are not 'worst-case' are suboptimal. For the trade-off between hitting limits and simulator realism, experts are needed to tune the MCA parameters. This expert tuning often involves using human-in-the-loop experiments to obtain a 'feeling' of what is optimal [50, 51].
In attempts to avoid this inherently subjective manual tuning, adjustments to the CWF have been made. With the Optimal Washout Filter (OWF) [52], for example, filter orders and parameters are optimized off-line using an optimization algorithm that minimizes

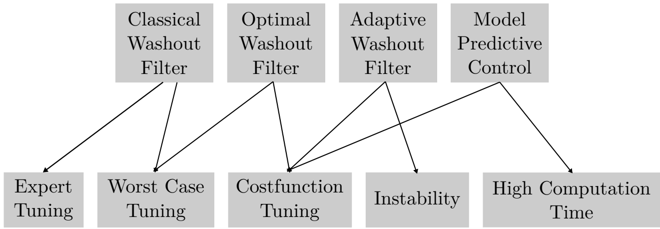


Figure 1.3: Challenges per MCA type.

a specific cost function. The cost function is often based on calculating the difference between vehicle and simulator linear acceleration and rotational velocities, but can also include models of, for example, the human vestibular system to account for thresholds in the human perceptual system [53]. With this type of MCA, however, the algorithm is again always tuned for the expected worst-case and the optimization needs to be repeated when different manoeuvres or vehicles are being simulated.

Adaptive Washout Filters (AWF) [54] were designed in another attempt to avoid global scaling. This MCA implicitly accounts for simulator limits by adjusting the filter gains in real time, based on minimizing a cost function that penalizes the difference between simulator and vehicle motions, the motion magnitude and the gain parameter change. It is a non-linear and much more complex procedure than the Classical or Optimal washout filters, but does not lead to significant improvements. Additionally, the adaptive filters are prone to instability, which, all together, makes that they are not widely used.

Lately, with increasing availability of computation power, MCAs based on model predictive control (MPC) [42, 55–57] have been introduced. Here a model of the simulator is used to predict the simulator motions for a given set of simulator inputs over a specified prediction horizon. By minimizing a cost function, the optimal simulator inputs for a given reference motion are found. Each time step the first simulator input is sent to the simulator, after which the optimization is repeated. With these MCAs the simulator limits are explicitly accounted for such that worst-case tuning is no longer needed, while algorithm stability is obtained with the combination of a well-designed cost function and a sufficiently long prediction horizon. Additionally, the cost function can be designed for optimal perceived simulation realism, by taking into account human percept.

In Figure 1.3 an overview of the different types of MCAs and their challenges are shown. From this figure it is clear that the one challenge that all types of MCAs share is the tuning of its parameters, may it be filter parameters or cost function parameters. Generally this tuning is done by experts, often using human-in-the-loop experiments. As these experiments are expensive and time consuming, often a limited number of parameter sets is tested [46, 58–61]. To make a well-grounded choice for the best MCA, it is imperative that these experiments provide a maximum of information on the cueing quality. Improving the MCA outside of the limited sets that are tested also requires knowledge on what causes the differences in perceived cueing quality.

1.2. Cueing quality

Simulator fidelity, simulation realism, MCA performance and cueing quality, are just a few of the terms that exist in literature that aim to capture how realistic a vehicle motion simulation is. Simulation realism can be influenced by many things, such as the quality of the outside visuals and sounds, the vehicle mock up and the motion cue quality. In this thesis the term cueing quality will only refer to the effect of the physical motion cues generated by a motion cueing algorithm on the perceived simulation realism. A high cueing quality thus results in a more realistic simulation than a low cueing quality, when all other simulator and experimental conditions are considered equal.

As here we consider *perceived* realism, high cueing quality does not necessarily mean that the vehicle motions need to be replicated one to one with the simulator motions. Using tilt-coordination to simulate sustained acceleration while applying below human perception threshold rotations, for example, can result in the same cueing quality as would a one to one sustained acceleration, because the human subject would not perceive the difference.

As the human sensory system is subject to noise, also differences between visual and physical motion cues in the same motion channel cannot always be distinguished. In fact, in [62] and [63] coherence zones, ranges which indicate how much a visual motion cue can differ in magnitude from a corresponding physical motion cue while still being perceived as coherent, were identified for different motion channels. In this thesis, the term **Perceived Motion Incongruence (PMI)** refers to visual-physical motion cue pairs that are outside of these coherence zones, i.e., that are not coherent or, more generally, not congruent. The level of PMI then refers to the magnitude of its effect on the simulator realism, i.e., motion cue pairs that are perceived as incongruent but not detrimental to simulator realism will have a lower PMI than motion cue pairs that are perceived as incongruent and very detrimental to simulator realism. In Figure 1.4 the mapping from vehicle motions to this PMI is shown schematically. The vehicle motions usually consist of lateral, longitudinal and vertical linear accelerations and rotational velocities in roll, pitch and yaw. The simulator presents these vehicle motions to the human via visual motion cues, which are similar to the vehicle motion cues, and via physical motion cues, which differ from the vehicle motion cues. The human senses these motions cues with its visual and gravito-inertial sensors. Given the instruction, the human can use its car driving experience and preferences to compare the visual-physical motion cueing pair to real vehicle motions and generate one percept of motion incongruence.

Much research has been done on when motion cue pairs, i.e., visual and physical motion cues, are perceived as different [64–68], as these differences can be the most detrimental to motion simulation, due to the fact that they can induce simulator sickness [69, 70]. But also if a motion cue pair has magnitudes that lie within a coherence zone, i.e., differences are small, it can still affect the cueing quality negatively. In this case, it is possible that the vehicle motion magnitude that is being simulated is perceived incorrectly. Most cue integration models, such as [71] and [72], show that the perceived magnitude of a motion is some weighted average of the motion cues perceived by the different sensory organs. If an physical motion cue is within the coherence zone of a visual motion cue, but lower, a weighted average would thus imply that the perceived motion is somewhat lower than the vehicle motion that is being simulated.

Another aspect of cueing quality is that it is *time-varying*. Generally, the magnitude of the differences between vehicle and simulator motions already vary over time, logically resulting in differences in cueing quality over time. But also when the magnitude of the difference between simulator and vehicle motions is similar, the cueing quality can

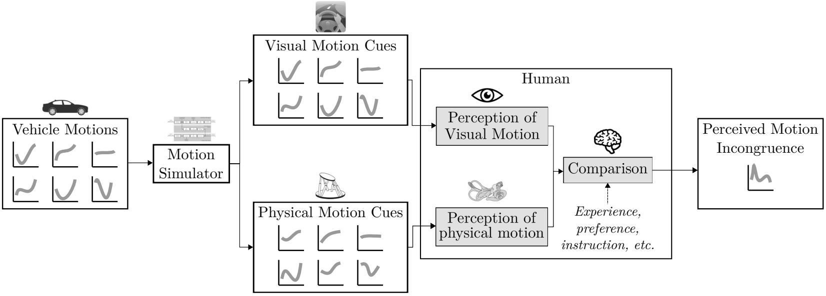


Figure 1.4: Scheme showing the mapping from vehicle motions to perceived motion incongruence in a motion simulator.

still differ. In [51] an overview is given of different cueing error types and their varying influences on the cueing quality. In Figure 1.5(a) an example of two of such cueing error types, a missing and a false cue, is shown. Both cueing errors have exactly the same objective quality, i.e., their euclidean distances are the same, as can be seen in Figure 1.5(b), but one is the result of *missing* motion, while the other is the result of *added* motion where no motion was expected. The false cue is known to be perceived as more detrimental to the cueing quality than the missing cue [51], as indicated in the fictional cueing quality detriment in Figure 1.5(b).
The quality of an MCA therefore strongly depends on how often the most detrimental cueing errors occur during a particular simulation. Information on the time variations in cueing quality is therefore essential when trying to understand why certain MCAs result in a low cueing quality, i.e., was there just one very detrimental cueing error or was the cueing quality constantly low? In the former case, the particular manoeuvre causing the large drop in quality could for example be removed, or if caused by hitting a limit, the gains can be scaled down. Knowing when a drop in cueing quality occurred can also help significantly in determining its exact cause related to the simulator motions.

1.2.1. Measuring Cueing Quality

Generally, a high quality MCA would cause the perception of being in a real moving vehicle, such that the participant behaves, i.e., controls the vehicle, in a similar way as in a real vehicle. For training purposes especially, it is important that the subject reacts to the perceived motions in exactly the same way as (s)he would in a real vehicle. One way of objectively measuring MCA quality is therefore to examine the control behaviour and compare it to control behaviour in a real vehicle, such as was done in [73] for flying and in [74, 75] for driving behaviour. This, however, is very time consuming and only a limited set of safe manoeuvres can be tested in this way.
Examining the difference in control behaviour with different MCA settings is also done, but it remains difficult to determine which control behaviour is desired without a real life example to compare it to. Another problem with examining control behaviour is that humans are very good at adapting [76], i.e., it is possible that the measured control behaviour in the simulator and real vehicle is similar, while the perceived motion differed. If this is the case during training, the participant would develop incorrect

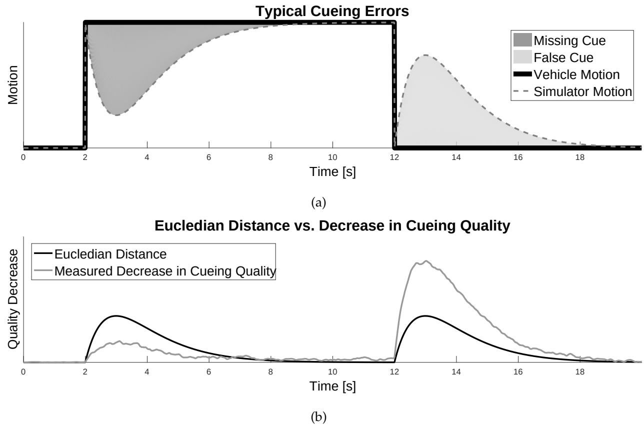


Figure 1.5: Simplified vehicle and simulator motions as the result of motion washout with corresponding cueing errors (a) and the fictional corresponding decrease in cueing quality and the actual euclidean distance between simulator and vehicle motions (b).

associations between certain perceived motions and their manoeuvres and, with that, fail to develop appropriate control behaviour.

Finally, a more practical issue with measuring control behaviour is that differences in control behaviour between participants will result in different motions between experiments. It is therefore difficult to perform a human-in-the-loop experiment where each participant is subjected to exactly the same motion cueing. Conclusions on differences in control behaviour are therefore generally made by analysing the behaviour over longer periods of time, and either fitting parameters of a control behaviour model to it [77] or averaging certain aspects [75, 78], such as control effort, over time. While this averaging over time can reduce the effects of small differences in motions between participants, it also removes all time information for the analysis. This time information, however, is particularly useful when analysing what caused the differences in MCA quality.

To avoid dealing with the adaptive nature of humans, one could try to measure the perceived motions or perceived cueing quality. As perception happens in the brain, however, it cannot be measured directly. Up till now the only objective measures related to cueing quality are physiological measures, such as measured in [79], showing simulator sickness. Simulator sickness, however, only occurs with very bad cueing quality and develops slowly over time, making it unsuitable to determine which part of the simulation really caused the sickness.

Instead, therefore, the perceived cueing quality is often measured subjectively. While subjective measures are generally disfavoured compared to objective measures due to their large variability, when obtaining a sufficient number of measurements, reliable results can be obtained. Many studies use subjective measurements such as questionnaires [36, 80], magnitude estimation [39] and paired comparison methods [81, 82] to determine cueing quality. While here a direct measure of the overall cueing quality is obtained, still important time information on when the cueing quality was high or low

is missing. While some have tried to include more time information via questionnaires [36], it remains difficult to directly relate such results to the provided visual and physical motion cues.
Finally, also off-line methods to determine MCA quality have been developed. Most of these methods, however, are related to the often used Classical Washout Filters. The Sinacori-Schroeder criterion [50], for example, determines acceptable gain and phase shift regions for the high-pass filter of a Classical Washout Filter. The Advani-Hosman criteria [83] instead provide such regions for the transfer function of the entire motion system. The more elaborate Objective Motion Cueing Test (OMCT) [84] uses similar criteria to determine the motion quality of the entire system, such that simulators can be compared. Both the Advani-Hosman criteria and the OMCT, however, assume a mostly linear system and analyse this system in the frequency domain. These methods are therefore suitable to compare systems using a Classical Washout Filter that keeps the motions within the simulator limits, but due to the lack of *time* information these methods are less suitable for highly non-linear MCAs such as the MPC-based MCA. Additionally, it is difficult to pinpoint exactly when or why an MCA has a lower quality.

1.2.2. Improving Cueing Quality

While each type of MCA can be improved on different aspects, as shown in Figure 1.3, one challenge that all MCAs face is parameter tuning for optimal cueing quality. While human-in-the-loop experiments can be used to determine the best out of a limited group of MCA settings, such as was done in [46, 58, 60], it is very time-consuming to use such experiments to actively tune the parameters. Instead, off-line methods, such as using the Sinacori-Schroeder criterion, Advani-Hosman criterion or OMCT, are often used to perform an initial analysis and tune the parameters. As mentioned before, however, these methods were designed for mostly linear algorithms, and are not suitable for highly non-linear algorithms such as MPC-based MCAs.
Analysing and improving the cueing quality of such highly non-linear MCAs is often done with MCA independent methods such as visual analysis of the resulting simulator motions for a specific set of test manoeuvres [7, 85, 86] or comparing different parameter settings using a cost function that takes into account the difference between simulator and vehicle motions [41, 87, 88]. While the latter method is very time efficient, its effectiveness depends on the choice of cost function.
Cost functions used for MCA optimization, either used within the algorithm itself or used as an analysis tool of its results, come in many different forms. The simplest version is a weighted sum of the (squared) differences between simulator and vehicle motions [40, 89]. While such cost functions are easy to implement in a cueing algorithm, they lack important information related to the perception of motion. In an attempt to include the perceptual system in such cost functions, many have instead first ran the simulator and vehicle motions through simplified models of our vestibular system [41, 53, 56]. Such models, for example, account for the washout effect on the rotational velocity of our vestibular organs, i.e., we do not perceive sustained rotational velocity [90]. By running the simulator and vehicle motions through such models before comparing them, differences between simulator and vehicle motions from simulating sustained rotational velocity with a washout filter would, correctly, not be penalized.
While many claim that including such models improve the perceived cueing quality [37, 41, 55, 91], not many have actually tested this. In [37] the influence of different perception models in two types of MCAs was only investigated off-line, by analysing

the algorithm responses, i.e., the effect of using different perception models on the perceived cueing quality was not investigated using human-in-the-loop experiments. Moreover, not only the perception models changed between conditions, but also parameter retuning was applied, making it difficult to identify the influence of perception model changes alone. In [37] human-in-the-loop experiments were done to evaluate some of the different types of cueing algorithms described in [37], however, here the focus was on differences between an optimal and a non-linear cueing algorithm, rather than differences between perception models. In [41, 55, 91] the effect of using vestibular models was not evaluated at all. In [92], however, human-in-the-loop experiment results were analysed using such vestibular system models and they concluded that comparing motions after running them through such models does not explain the experiment results better than simply comparing the original motions signals.
Research has also been done on using more elaborate perception models that, for example, include models of the visual system [37, 93]. For now these models mainly contain low level sensory systems and not the higher level cognitive functions of the brain related to motion perception. While such models can be useful for gaining a better understanding of human motion perception, they only map actual simulator motions to perceived motions, and do not determine how this effects the perceived cueing quality. For example, they do not provide information on how to weigh and combine cueing errors between perceived vehicle and simulator motions from different motion channels into one measure of cueing quality. As also stated in [59], rather than the use of vestibular models, the cueing quality results of an optimization of any algorithm mainly depends on the choice of cost function and corresponding weighing constants. Moreover, current motion perception models cannot explain why different cueing error types, such as scaled and false cues, are not equally detrimental to the cueing quality. While the model driven bottom-up approaches are very useful in fully understanding how we perceive self-motion, they are not yet directly applicable to the problem of predicting cueing quality.

1.3. Research Goals

The mapping of vehicle motions onto the simulator workspace, while maintaining a high simulation realism, remains one of the main challenges in vehicle motion simulation. To make an *MCA-independent* method to analyse *time-varying* motion cueing quality *off-line* is important when trying to improve cueing quality and the effects different types of cueing errors have on this quality, but is currently not yet available. The research goal of this thesis is therefore:

To develop an MCA-independent off-line prediction method for time-varying perceived motion incongruence during vehicle motion simulation, to improve motion cueing quality

The focus is put on Perceived Motion Incongruence (PMI) as the differences between visual and physical motion cues are assumed to be the most detrimental for simulator realism. No specific MCA type is assumed, such that any developed prediction method will be MCA-independent. The aim of the PMI prediction method is that it can be used for tuning of MCA parameters, such that the resulting motion cueing quality can be optimized.

1.4. Approach

The research goal is addressed in three steps: *measuring*, *modelling* and *minimizing* perceived motion incongruence. The thesis aims to provide a complete roadmap that describes how to *measure* and *model* PMI and how to apply such models to predict and with that *minimize* PMI in motion simulations.

Measuring time-varying PMI is essential for the development of PMI prediction models. While measurement methods such as paired comparison might be used to measure overall PMI, no method exists yet that can measure the time-varying aspect of PMI. As a first step in this thesis, a subjective method to measure time-varying PMI during a passive driving experiment was therefore developed and validated with two human-in-the-loop experiments. For subjective measurements the accuracy of the measurement strongly depends on the number of participants. As more participants with driving experience are available than, for example, with piloting experience, all experiments in this thesis are performed with car driving simulations.

The data obtained in the experiments were subsequently used for the development of a method to design data-driven PMI prediction *models*. A data-driven top-down modelling approach was chosen, as this would lead to the goal of PMI prediction more efficiently than a model-driven bottom-up approach. Via a data-driven approach the focus of the model automatically steers to those aspects of perception that influence PMI most. A model-driven approach, on the other hand, would require modelling all aspects of human self-motion perception and cognition, including those aspects that may not significantly affect simulator realism.

The developed models were subsequently analysed with respect to their explanatory and prediction power. For the analyses of the prediction power, first a prediction of new data within one experiment was made. Next, a method to compare PMI rating data between experiments was developed and used to analyse the prediction power of the PMI models between experiments.

While off-line PMI predictions can directly be used to *minimize* PMI via manual tuning of MCA parameters, a more efficient use of PMI prediction models would be to implement them in MCA optimization algorithms. Hence, in the last step of this thesis approach a simple PMI prediction model was implemented as the cost function of an optimization-based MCA, and its effectiveness was analysed in a human-in-the-loop experiment.

1.5. Scope

As simulator realism and the corresponding motion cueing quality have many aspects, a number of assumptions to limit the scope of this thesis were made.

First of all, it is assumed that humans can make a reasonable comparison between vehicle and simulator motions while experiencing a vehicle motion simulation. For this comparison it is assumed that the vehicle motions are perceived via some combination of visual cues and prior experience in car driving. For this reason, only participants that were in the possession of a valid driving license were allowed to participate in the experiments.

Assuming that vehicle motions can accurately be perceived from visual information and experience disregards important aspects of human self-motion perception. Visually perceived motion is strongly influenced by aspects such as field-of-view [94, 95] and visual scene content [95, 96]. Additionally, not all motions can be perceived with the same accuracy. As the measurement method developed in this thesis only involves

passive driving, i.e., the participant is not requested to provide any vehicle control inputs, also the influence of car driving style experience on the perceived motion is significant. Expected car motions that are difficult to derive from visual cues, such as longitudinal acceleration, might be influenced by the driving style of the participant which likely differs from the driving style of the 'automatic driver' used in the experiment. For those motions extra care should be taken when deriving conclusions from the corresponding PMI measurements. It is, however, expected that in general the visual motion cues are sufficient to derive a reasonable estimate of the vehicle motions.
A second assumption is that the time-variation of cueing quality is purely due to the time variation of the inputs, and that any PMI prediction model itself is therefore time-invariant. It is likely that some time variation is present in the human perception system, for example, due to the changing physical state of a participant related to fatigue or stress. However, by properly instructing the participant to, for example, take breaks before loosing focus, minimizing the experiment duration, and averaging over multiple measurements of PMI, such time variations are expected to be small when compared to the time variations caused by inputs.
A third assumption is that the PMI measurement is a good indication of the cueing quality of the vehicle motion simulation, and minimizing the PMI would thus improve cueing quality. This measure only includes perceived incongruences between vehicle and simulator motions, while congruent motion cue pairs that result in incorrectly perceived vehicle motions are not measured. While PMI is not the only aspect of cueing quality, any incongruences between vehicle and simulator motion negatively affect the cueing quality and can thus be taken as a measure of cueing quality.

1.6. Outline

The first two chapters of this thesis are based on scientific publications, while other chapters are written to be included in this thesis first. All chapters can be read independently, although some back references occur. All nomenclature and references to literature are made uniform throughout the thesis.
The thesis is divided in three parts: measuring, modelling and minimizing perceived motion incongruence. In Figure 1.6 a schematic overview of the thesis is shown. It has a sequential structure, with each chapter providing data and/or developments for the next chapters. Part I yields a PMI measurement method and corresponding data sets. In Part II these data are used for the development of a PMI model. Part III uses both the developed measurement method, and a PMI model to optimize an MCA.
Chapter 2 introduces a newly developed subjective method based on continuous rating to measure time-varying PMI. The resulting motion incongruence rating is checked for reliability and validity in a human-in-the-loop experiment. Data collected in this experiment are also used in Chapters 4, 5 and 6.
Chapter 3 compares an optimization-based MCA, developed at the MPI for Biological Cybernetics, to the MCA used by the Daimler motion simulator which is based on classical washout filters. The two MCAs are evaluated using both the newly developed rating method, to determine its performance, and an off-line analysis describing the different strategies used by each MCA. The rating data from this experiment are also used in Chapter 6.
Chapter 4 addresses the varying influences which different cueing error types can have on cueing quality. A cueing error detection algorithm is developed using data from Chapter 2 and tested using data from an experiment performed outside this thesis, re-

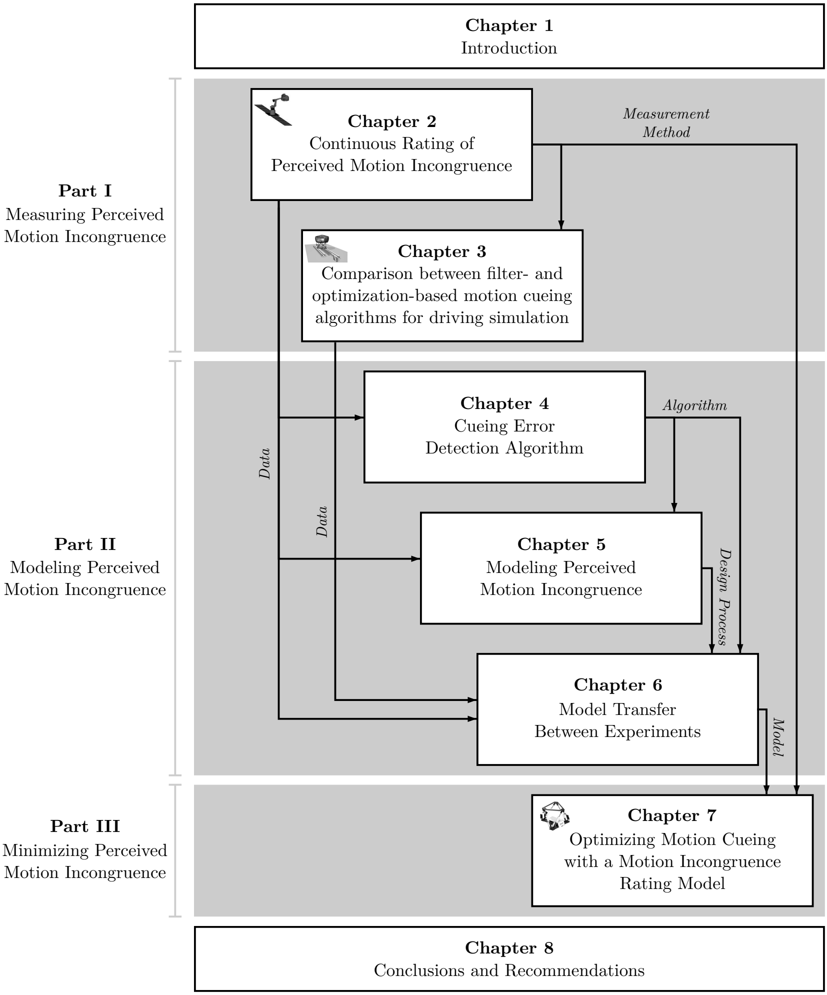


Figure 1.6: Thesis outline.

ported in [97].
Chapter 5 presents a system identification process for the development of PMI models. The algorithm developed in Chapter 4 is used in the non-linear part of such PMI models.
Chapter 6 shows how motion incongruence ratings from different experiments can be used to analyse the prediction capability of PMI models, or can be properly aggregated into a larger dataset. The introduced Model Transfer parameter is validated, and different PMI models are parametrized and analysed using data obtained in Chapters 2 and 3.
Chapter 7 describes the implementation of one of the PMI models from Chapter 6 as a cost function in an optimization-based MCA. The performance of this new cost function is compared to the original cost function using motion incongruence rating results of a human-the-loop experiment.
The thesis ends with conclusions and recommendations for future research.

2

Continuous Subjective Rating of Perceived Motion Incongruence during Driving Simulation

In this chapter a method is presented to measure Perceived Motion Incongruence (PMI) continuously throughout a motion simulation. The method, which is based on continuous rating, was validated in an experiment. Subjects were requested to continuously provide a subjective rating of PMI during a vehicle simulation in the CyberMotion Simulator through constantly adjusting a rotary knob. Participants demonstrated that they could rate repetitions of the same simulation consistently. The resulting time-varying ratings were consistent with overall ratings of the same simulation and with literature on the typical cueing error types presented in this experiment. The time information contained in the rating data obtained with this method is essential for development of PMI prediction models as described in Chapter 5.

This chapter is based on the following publication:
Cleij, D., Venrooij, J., Pretto, P., Pool, D. M., Mulder, M., and Bülthoff, H. H. (2017). "Continuous Subjective Rating of Perceived Motion Incongruence during Driving Simulation." in *IEEE Transactions on Human-Machine Systems*, vol. 48, no. 1, pp. 17-29

2.1. Introduction

Motion-based vehicle simulators are used for a wide variety of applications. They are an increasingly important tool for training, research and vehicle system development in both the car [98] and aerospace industry [1]. However, one of the main challenges in motion-based simulation is to cope with the typically limited workspace of the simulator. To map the vehicle physical motions onto the simulator motion space, a Motion Cueing Algorithm (MCA) is used [85]. As the simulator motion space typically is much smaller than the vehicle motion space, this process inherently results in motion mismatches: differences between the unconstrained visual and the constrained physical motion cues. These mismatches result in a decrease of simulator motion fidelity and unrealistic simulations [51].

For motion simulation fidelity, a distinction is made between physical and perceptual motion fidelity [99]. Physical fidelity is defined as the match between objectively measured motion cues in the simulator and in the vehicle. Perceptual fidelity is defined as the match between simulator and vehicle motion cues as perceived by the human. The main reason for using a vehicle simulator is not to replicate the physical vehicle motions, but rather replicate the human perception of these motions [100]. Van der Steen [62] investigated the effect of physical incongruence between visual and physical motion on the perceived realism of the combined motion in a passive flight simulation. He introduced the term coherence zone for the range of physical motion amplitudes that were still perceived as coherent with a given visual motion amplitude. In [101] the effect of motion frequency on these coherence zones in passive flight simulation is investigated and in [102] the term phase coherence zone is introduced as the range of phase shifts for which physical and visual motion are still perceived as realistic. As in real vehicles, where all motion stimuli are congruent, motion simulators should provide physical motions that are within these coherence zones. If this is not possible, at least the perceived incongruence between different motion stimuli should be minimal. The current study therefore focuses on measuring any, linear or non-linear, incongruence between visual and physical motion that is perceived in a passive vehicle simulation. The degree to which this incongruence results in unrealistic motion is hereby called the Perceived Motion Incongruence (PMI).

To improve motion cueing we need to understand how this PMI is related to the physical motion mismatches presented in the simulator. Currently there are methods to directly or indirectly measure PMI, but they only provide time-invariant overall results. These discrete results can be used to quantify and compare the overall quality of an MCA, but cannot be correlated to the time-varying short-duration motion mismatches. It therefore remains unclear which motion mismatches are responsible for the overall PMI. A time-varying measure of PMI, that can be correlated to these mismatches, is therefore needed. Relevant motion mismatches can then be identified and, eventually, minimized. Besides being instrumental to improve motion cueing, such a measure can also be used to gain a better understanding of human motion perception.

Perceptual fidelity is measured using human-in-the-loop experiments. During these experiments participants are usually subjected to vehicle simulations using different MCA tunings. This fidelity can currently be measured directly via questionnaires or subjective ratings on the MCA quality. In [36] information on MCA quality during car motion simulation was obtained via questionnaires after each simulation run and overall MCA quality ratings at the end of the experiment. In [80] the Simulation Fidelity Rating scale together with an overall Motion Fidelity Rating were used to subjectively rate the motion fidelity of a helicopter motion simulation for different MCAs. In both