INCREMENTAL CALIBRATION OF SEAT SELECTION PREFERENCES IN AGENT-BASED SIMULATIONS OF PUBLIC TRANSPORT SCENARIOS

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ABSTRACT

The calibration of agent-based pedestrian simulation models requires empirical data. To avoid cost-intensive real-world experiments, human-in-the-loop simulations can be applied in which simulated pedestrians interact with human-controlled agents. However, the experiment results may be unrealistic if the human participants are presented with agents acting according to an uncalibrated model. We propose an incremental calibration approach that aims to address the circular dependency between the behaviour of human and simulated pedestrians. By incrementally adapting the parameters of the simulated agents to match the behaviour of the human participants, we aim to gradually approach a realistic interaction. We evaluate our approach using the simulation of the boarding procedure of a public transport vehicle in 2D and virtual reality experiments. The calibration results are compared with those gathered from a traditional non-incremental calibration. Our results indicate the feasibility of our approach and highlight the necessity for future research on efficient simulation model calibration.

1 INTRODUCTION

Crowd simulation is a helpful tool to study pedestrian flows in a variety of contexts, e.g., in evacuation scenarios (Pelechano and Badler 2006), in urban planning (Farenc et al. 1999), or to understand passenger movement in public transport systems (Gao and Jia 2016). One method to simulate crowds is to follow an agent-based approach, i.e., each pedestrian autonomously employs a sense, think, act cycle (Hoogendoorn 2001). The agent senses its environment and other agents, computes actions according to a model and carries out the actions. There exists a wide range of different behavioural models, e.g., the magnetic force model (Gipps and Marksjö 1985), the Social Force model (Helbing and Molnar 1995), or cellular automata models (Blue and Adler 2001), that aim at reproducing realistic pedestrian movement.

Applying an easy-to-understand and manageable general-purpose model to realistically simulate crowd movement seems to be intractable, as human behaviour is complex and affected by various factors, e.g. their psychological state and the current context (Sakuma et al. 2005). Therefore, these models usually have a variety of input parameters that can be calibrated in order to adapt the model to a specific scenario. Calibration is commonly done with the help of empirical data, such as trace files of pedestrians or video footage. The calibration process proceeds by setting the input parameters in a way so that the employed model reproduces the empirical data as closely as possible.

Often, the problem is the availability of this empirical data. Real-world experiments are costly and time intensive as they require a physical environment and possibly a large number of test subjects. High quality (in terms of resolution and frame rate) video footage alleviates this problem, however, the observed

behaviour might not generalise easily and is restricted to already existing environments. On top of that, comprehensive video footage of public spaces can be hard to obtain due to prevailing data-protection laws.

One possible solution is to immerse human participants in a virtual reality (VR) environment populated with simulated pedestrians (Shendarkar et al. 2006). The benefits of virtual environments are that the scenario conditions can be changed at low cost and the collection of data is straight forward as the experiment is already of digital nature. When the goal is to calibrate the behaviour models of the simulated agents using the behaviour of the human participant, a causality dilemma arises: the simulated agents will affect the human participants in an unrealistic manner, leading to potentially implausible behaviour of the human participant which is then used to calibrate the simulated participants. For instance, if the simulated agents in an evacuation scenario choose exit routes unlikely to be chosen by a human participant, the participant may be able to follow a fixed preferred route. Thus, more complex decision-making based on dynamic properties such as the current crowd density on different exit routes would not be observed.

To approach this problem, we propose a dynamic data-driven calibration approach in which the behaviour of the simulated agents is gradually and iteratively calibrated to the observed behaviour of the human participants. By continuing the experiment during the calibration process, we aim to create a feedback loop: the human participant reacts to simulated pedestrians that exhibit increasingly realistic behaviour, causing the human participant to also behave in a more realistic manner. Our contributions can be summarized as follows:

- **Incremental calibration method**: We propose a method for the incremental calibration of agent-based pedestrian models using human-in-the-loop experiments.
- **Proof of concept**: We show how our method can be applied by demonstrating its applicability to the calibration of a seat-selection model for public-transport vehicles.
- **Comparison to traditional approaches**: We show that the incremental calibration leads to different results than a calibration in the presence of uncalibrated simulated agents.

While our results do not yet allow us to make statements about the relative quality of the results of the incremental and offline calibration, the substantial differences in the calibration results indicate that further investigation is warranted. The remainder of the paper is structured as follows: In Section 2 we give a comprehensive overview of related works in the domains of crowd simulation and virtual reality. We explain our general methodology in Section 3 and our specific experiment setup is described in Section 4. We present and discuss our results in Section 5, which is followed by a discussion on the limitations and challenges of the presented approach in Section 6 before concluding in Section 7.

2 RELATED WORK

In the following, we give an overview of existing works on the parametrization of pedestrian models based on real-world data and optimization approaches. Subsequently, we discuss works on model calibration based on observations in virtual reality environments.

2.1 Parametrization of Agent-Based Pedestrian Simulation Models

In agent-based pedestrian simulation, modelling pedestrians is achieved by representing them as autonomous entities that independently react to their environment according to a set of decision-making rules (Zhou et al. 2010). Frequently, agent-based pedestrian simulation models are applied to study scenarios in the context of public transportation, e.g., to evaluate different bus or train layouts with respect to passenger flow and the required dwell time at stations (Gao and Jia 2016; Rexfelt et al. 2014; Schelenz et al. 2012; Schelenz et al. 2014), or to evaluate station layouts (Hoogendoorn et al. 2004).

Hoogendorn differentiates three levels of pedestrian movement covered by agent-based pedestrian models Hoogendoorn 2001, summarized in Parisi et al. 2009: the *operational* level addresses the basic

walking behaviours, the *tactical* level performs basic planning such as route choices, and the *strategical* level covers higher-level planning.

One of the most common models on the operational level is the Social Force model proposed by Helbing in the context of simulating evacuation processes (Helbing and Molnar 1995). The model computes for each agent an acceleration based on repulsive forces computed from the neighbouring agents' distance and mass. In the present paper, we rely on the Social Force model for basic walking behaviour and on simple rules on the tactical and operational levels (specified in Section 4).

While crowd simulation models determine the general behaviour of agents, their mathematical formulation typically contains a number of parameters for which suitable numerical values must be found according to a given scenario. For instance, on the operational level, the Social Force model has multiple parameters, some of which lack a direct interpretation, complicating the prediction of the effects on the observed agent behaviour (Kretz et al. 2017). On the strategical level, parameters for the agents' decision-making must be configured, e.g., their preference for a certain seat inside a train (Schelenz et al. 2013), the movement and decision making on the platform before boarding the vehicle (Daamen and Hoogendoorn 2004), and the passengers' choices of destinations and routes (Alam and Werth 2008).

(Kretz et al. 2014) investigate how a user equilibrium can be reached when calibrating pedestrian models for a given scenario. The authors limit the route choices to a limited number of fixed routes generated from the scenario geometry. (Crociani and Lämmel 2016) simulate pedestrian movement on a cellular grid and achieve a user equilibrium or system optimum, depending on the cost function used to make route choices.

Methods that aim to achieve a system optimum or user equilibrium do not require empirical data, and it has been argued that the results still reflect some of the properties of real-world systems. However, the results do not reflect the effects of non-optimal decision-making, e.g., due to social factors (Kretz et al. 2014).

To calibrate pedestrian model parameters to real-world observations, most existing work relies on video footage Berrou et al. 2007;Hoogendoorn et al. 2003. Video footage is either collected during regular operations or from dedicated experiments with volunteer participants. Sometimes, physical mockups are constructed to serve as the environment for the experiment (Rexfelt et al. 2014).

Kretz et al. (2017) provide guidelines on how to calibrate the parameters of the Social Force model against empirical data. The suggested calibration process is an algorithm that determines suitable parameters according to the general relationships between the model parameters and the output statistics. The process is iterative and includes feedback, i.e., simulations are performed to determine the next change in parameters.

Rudloff et al. (2011) calibrate a model of passengers boarding and alighting a subway train against video footage gathered in experiments using a mockup of the subway train door area. They collected the times when passengers pass the train door, as well as the location of the pedestrians. Three sets of parameters are calibrated: the positions of passengers while waiting to board, parameters guiding the starting times of the boarding and alighting, and the parameters of the Social Force model. A simulation-based optimization process relying on a genetic algorithm was applied for calibration. The main part of the objective function is the absolute error between the crossing times of the passengers in the video footage and in the simulation.

Benner et al. (2017) calibrate a simulation model of pedestrians passing through a narrow corridor against trajectory data from a real-world experiment. They varied the Social Force parameters to fit the number of pedestrian within the corridor. Since a reasonable fit could not be achieved this way, the model was extended to include sets of agents with different desired velocities.

Voloshin et al. (2015) perform a simulation-based optimization to calibrate parameters of the Social Force model against video footage of pedestrians at a metro station. A simulation-based optimization process using a genetic algorithm is used to adapt the parameters. The objective function determines the error with respect to the number of agents, the flow, the passage time, as well as the number of overlaps among pedestrians and between pedestrians and obstacles.

The main difference between the discussed related work and our approach is that we assume that insufficient empirical data is available to calibrate the system. Our approach focuses on extracting calibration data from virtual reality experiments when only a limited number of participants is available and simulated agents are needed to populate the system.

2.2 Pedestrian Model Calibration in Virtual Reality Environments

Collecting calibration data from real-world experiments is time consuming and costly. In some existing works, experiments with human participants immersed in a virtual-reality environment were performed to gather the data required for calibration.

Shendarkar et al. (2006) gather pedestrian behaviours in an emergency response scenario from human-in-the-loop experiments in a virtual-reality environment. The observed behaviours are used to parametrize agent behaviours modelled using the Belief, Desire, and Intention (BDI) framework. In the simulated emergency scenario, agents escape a scene made up of paths with multiple intersections and obstacles. Path choice weights were directly gathered from the observed frequencies in the human-in-the-loop experiments.

Kretz et al. (2011) gather path choices of pedestrians when presented with a choice of multiple doors with varying numbers of other pedestrians inside a virtual reality environment. They avoid the need for human participants for creating congestion at the doors by relying on simulated agents. Agents behaved according to the Social Force model and the "dynamic potential" model for determining the desired direction and velocity.

The existing literature relies on "offline" calibration approaches, i.e., modifications to the parameter combinations are applied to the simulated crowd only after the experiment. In the above works, this approach is sufficient since there is only limited feedback with respect to the parameters being calibrated, i.e., adapting the crowd behaviour according to new observations would not affect the human participants' behaviour strongly. However, we argue that when the crowd model parameters to be calibrated may affect the human participants' behaviour, the partial calibration results should be fed back into the experiment.

3 INCREMENTAL CALIBRATION APPROACH

In the following, we describe the proposed approach on the example of a model calibration for simulating passengers boarding a public transit vehicle and selecting a seat. Figure **??** illustrates the building blocks and calibration work flow. The overall goal is to gather observational data of the human participant's behaviour in order to parametrise an agent-based pedestrian model so that seat selection preferences are represented in a realistic manner.

To this end, human participants as well as simulated agents share an environment and are repeatedly assigned the task of boarding a public transport vehicle starting from a randomized position near the vehicle door. We refer to each repetition as a *calibration cycle*. Each calibration cycle starts with participants and simulated agents starting to move from the outside of the vehicle to the inside and select a seat. The calibration cycle ends when each agent and participant have found a seat or a maximum time has passed. At this point, if an agent or the participant is still moving, they are considered standing. The simulated agents may affect the human participant's behaviour by occupying some of the seats or by obstructing some areas and paths inside the vehicle. In the first calibration cycle, the simulated agents perform their actions according to parameter values chosen manually, e.g., based on a domain expert's estimation, using empirical data from similar experiments, or entirely at random. The actions of the human participants as well as the simulated agents during a *calibration cycle* are monitored and stored as an *observation*.

After the boarding task has been completed by the human participants, a new parametrization of the simulated agents' behavioural model is produced by an *aggregator* to reflect the new knowledge gained about the participant's behaviour. Depending on the type of the considered parameters, the parameter values can be derived directly from the observations, e.g., the frequency at which a specific seat is selected over multiple calibration cycles. In other cases, there may not be a trivial relationship between the observations

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and agent parameters that lead to similar behaviour. Then, a black-box optimization may be performed at each optimization cycle or periodically to determine a suitable parameter combination.

There are various options for adapting the parameters at the end of each calibration cycle. In the simplest case, the parameters that match the most recent observation are used in the next cycle. However, to avoid oscillation, it may be necessary to also consider the parameter combinations matching previous observations, e.g., by computing a weighted average over all cycles.

Over the course of the calibration process, the human participant interacts with agents that more and more closely imitate the participant's previous behaviours. Through the resulting feedback, we aim to allow the human participant to gradually exhibit more realistic behaviours, improving in turn the realism in the behaviour of the simulated agents.
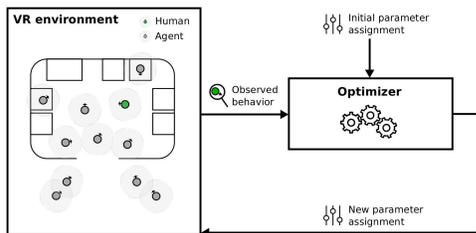

Figure 1: Entropy of the seat selection frequencies for participant 3, with slightly lower entropy compared to incremental calibration.
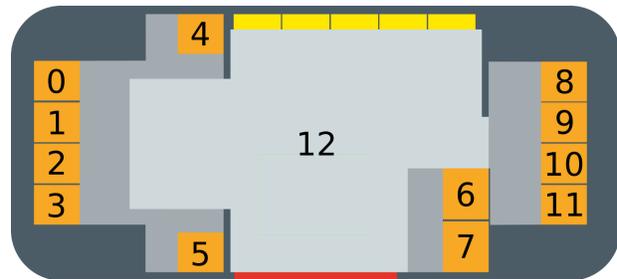

Figure 2: Incremental calibration approach: the agent parameters are adapted incrementally according to observations of the human participant's behaviour.

4 EXPERIMENT SETUP

In our experiments, a human participant repeatedly boards a public transport vehicle while the seat preferences of the simulated agents are incrementally calibrated to the observed preferences of the participant. The vehicle's interior design and layout used in the experiments is similar to upcoming autonomous vehicles to be used in autonomous public transport. Since currently, there are very few examples in which autonomous public transport vehicles are already in extensive use, pedestrian simulations may be applied to evaluate the effects of different vehicle interior layouts on the boarding and alighting times of passengers. The vehicle layout used in our experiments is shown in Figure 2. Different areas within the vehicle are signified by their colours. The seats are numbered, index 12 signifying any position in the standing area. At the end of multiple calibration cycles with many human participants, the agents should exhibit behaviours similar to humans entering a public transport vehicle.

We perform the experiments with respect to two different representations of the scenario: In the **2D top-down seat selection**, the participant controls a passenger in a 2D representation of the boarding scenario. In the **VR immersive seat selection**, the participant performs the boarding in a 3D environment using a head-mounted display (HMD) and a hand-held controller. In both environments, we focus on calibrating the seat selection preferences, while future work includes calibration of the Social Force parameters, which guide the distance-keeping between agents. For simplicity, we assume that the vehicle is empty when the boarding process starts and that the seat selection preferences can be expressed solely by the probabilities to select the different seats. We conducted the experiment with only a single human participant at a time, each participant experiencing the same scenario. Performing multi-participant experiments will require considerations of the weighting of observations and the generation of multiple agent types, which we leave to future work. After each human participant has gone through both calibration processes, the experiment is replicated with a different person. In effect, the outcome of each calibration process is a parametrization of the seat selection assuming that all agents share the preferences of the human participant.

Each *calibration cycle* terminates once all simulated agents have chosen a position in the vehicle. Both the 2D and the VR experiment rely on the same agent behaviour, which we modelled using the simulation

framework CrowdTools (Luo et al. 2009). The movement of the simulated agent is performed using the Social Force model (Helbing and Molnar 1995), with path planning according to the shortest path to the selected seat. The data from the observations is aggregated in a simple fashion: we form a histogram of the participant's seat selection frequencies. The histogram is updated with one additional observation after each calibration cycle. The seat selection probabilities for the simulated agents are produced by normalising so that the sum of all frequencies is 1. At the start of each cycle, the probabilities are updated. Both the simulated agents and the human participant are assigned randomised positions near the vehicle door.

2D top-down seat selection: In the 2D top-down seat selection (Figure 3a), the participants can see a top-down view of the vehicle and some surrounding space. One of the agents (represented by circles) is controlled by moving the mouse in the desired direction. Once the participant is satisfied with the position, the seat selection is terminated by pressing a mouse button, after which the agent can no longer be moved. Simulated agents move until they have reached their desired position or the maximum time has passed.

VR immersive seat selection: In the VR immersive seat selection (Figure 3b), participants wear a *head-mounted display* (HMD) to conduct the experiment in a virtual reality environment. The participant selects the direction of movement by rotating a controller and holds a button to move in the given direction. A calibration cycle is terminated once the participant indicates verbally that the current position is satisfactory.

The experiments were performed by 9 human participants aged between 22 and 30, three of which were female, six of which were male. In addition to the experiment data, a questionnaire collected data about the public transport travel patterns and familiarity with public transport. The main question asked in the questionnaire was how often the participants rely on public transport. 8 of the participants answered *daily*, while the remaining participant answered *2-3 times a week*. After the experiment, the participants were asked what they based their seat selection on. Common answers included: proximity to windows and exits, sitting in the direction in which the vehicle is going (right to left), distance to other agents (e.g., expectation to sit alone, one seat in between passengers).
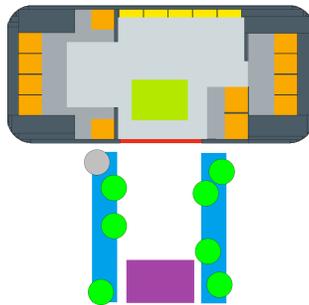
(a) Simple 2D mouse-controlled application.   (b) Virtual reality using an HMD and a controller.

Figure 3: Screenshots of the two virtual environments.

5 RESULTS

The two main questions we aim to answer in our evaluation are: 1. Are the seat selection preferences affected strongly by the choice of 2D or VR environment? 2. How do the measurement results differ between the experiment with uncalibrated agents and the incrementally calibrated agents?

5.1 Seat Selection Preferences

We first consider the results from the 2D experiments. Figure 4 shows how the seat selections of two participants evolved over the course of the experiment. We show the results both for uncalibrated agents and incrementally calibrated agents. The plots show the relative frequency for the human participants to occupy a certain seat after a given number of calibration cycles. Visually, we can observe that a larger

variety of seats were selected when agents were calibrated incrementally. This general trend was observed for a number of participants and will be quantified in Section 5.2.

(a) Participant 1: uncalibrated.

(b) Participant 1: incremental.

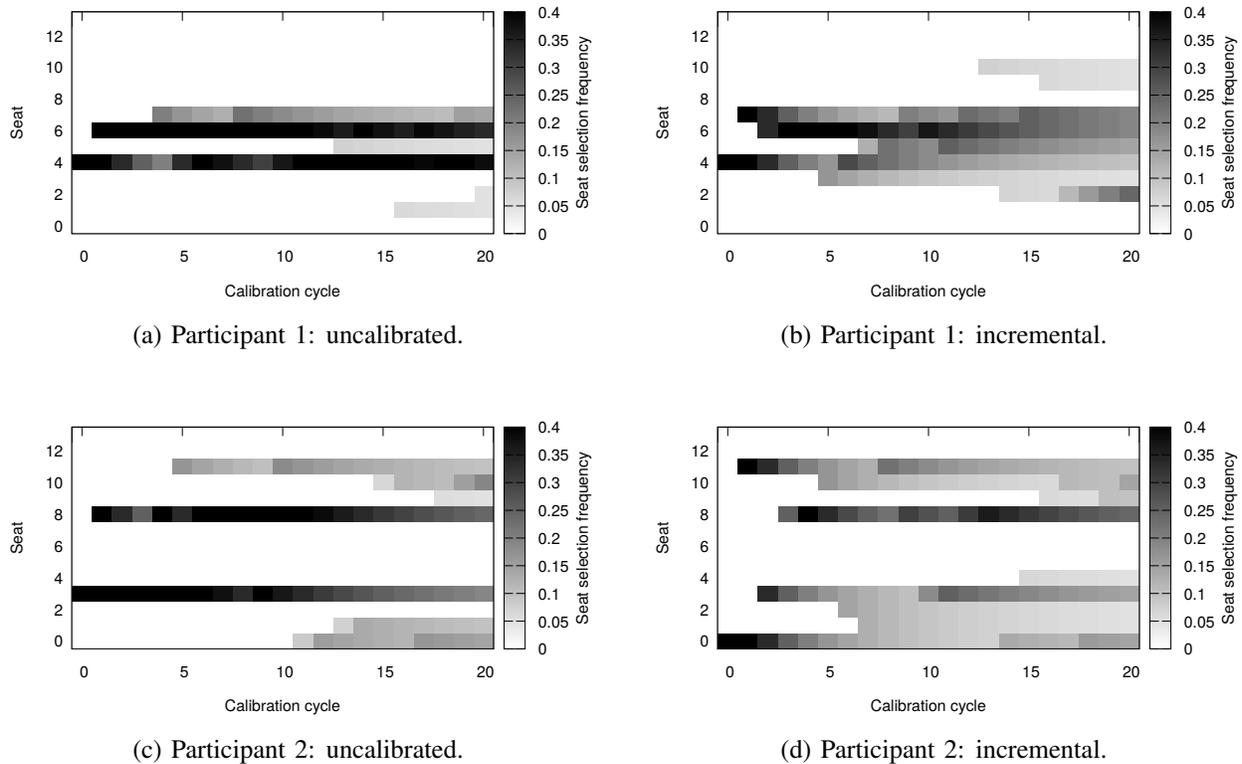(c) Participant 2: uncalibrated.

(d) Participant 2: incremental.

Figure 4: Example of the seat selection frequencies over the course of the experiment for two participants.

Looking at the seat selection probabilities at the end of the experiment, we observe that with uncalibrated agents, the diversity in the seat selection by the human participant is quite limited and that the probability distribution of the seats seems wider when agents are calibrated incrementally. Since the incrementally calibrated agents adopt the behaviour of the human participants, there is higher competition for the most preferred seats. These results indicate that the incremental calibration helps expose secondary preferences that are expressed only when the most preferred seats are favoured by other passengers as well.

5.2 Entropy of Seat Selection Frequencies

The entropy of the probability of selecting a specific seat in each calibration cycle can be used to describe the statistical dispersion of the observed seat probabilities. The entropy is maximal when all seats are equally likely and minimal when the probability of one particular seat is 1.

In Figure 5 two different participant's entropies over all calibration cycles can be seen. In both cases, the participants' seat choices were more diverse with the incremental calibration. In contrast to these results, in Figure 6 the incremental and calibrated entropy values do not differ significantly, i.e., the diversity in the participant's seat selection was barely affected when agents competed for the same seats. Figure 7 shows a ranked list of entropy differences between the calibration approaches for each participant after the last calibration cycle. It can be observed that the entropy difference is positive for all but one participant, i.e., the choice of seats became more diverse using the incremental calibration approach. This is caused by agents competing for the same seats as the human participant would, frequently forcing the human participant to choose a different seat. Lastly, we compared the results obtained using the VR environment
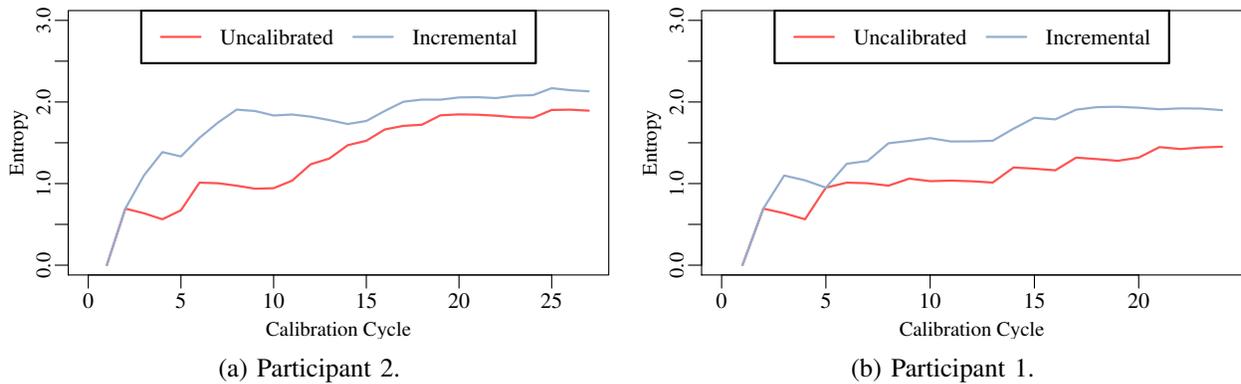
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(a) Participant 2.

(b) Participant 1.

Figure 5: Entropy of the seat selection frequencies in the 2D experiment over the calibration cycles for two different participants with and without incremental calibration.
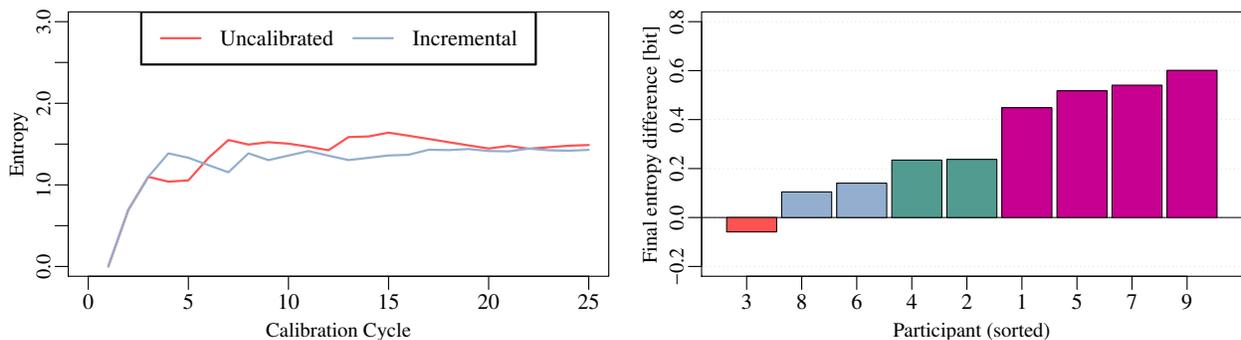

Figure 6: Entropy of the seat selection frequencies for participant 3, with slightly lower entropy compared to incremental calibration.

Figure 7: Sorted final entropy difference between uncalibrated and incrementally calibrarated agents. Colouring according to k-means, $k = 4$.

to the ones obtained using the simple 2D interface. Figure 8 shows the Bhattacharyya coefficient of the seat selection probabilities over the calibration cycles. A value of 0 indicates that there is no overlap between the two distributions, a value of 1 signifies that both distributions are identical. We observe that the results with both methods are similar but not identical, emphasising the influence of the chosen experiment setup. This is further illustrated by the histogram over all approaches shown in Figure 9 The popularity of some seats can be observed across all setups, with the aforementioned differences of the uncalibrated approach.

6 DISCUSSION

This article can only be a first step towards incremental calibration of agent-based models using a human-in-the-loop approach. Some of the open issues are of a general nature, others specific to the use case of seat selection in public transport vehicles. When setting up experiments with humans in virtual environments, there are several challenges: First, the design of the experiment itself can have a significant impact on the outcome, e.g., how the starting conditions are chosen as well as the look and feel of the virtual environment. Second, the number of iterations may be larger than the number a participant is willing to carry out. We observed that even after 50 iterations, there was still visible change in the seat selection behaviour for some of the participants. Potentially, faster convergence may be achieved by starting the experiment with partially trained agents or by weighting recent observations higher, although preliminary experiments indicated that the latter introduces large variations. Techniques from the field of Serious Games (Rüppel
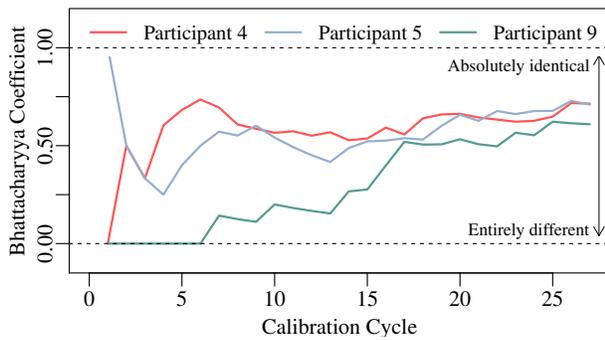
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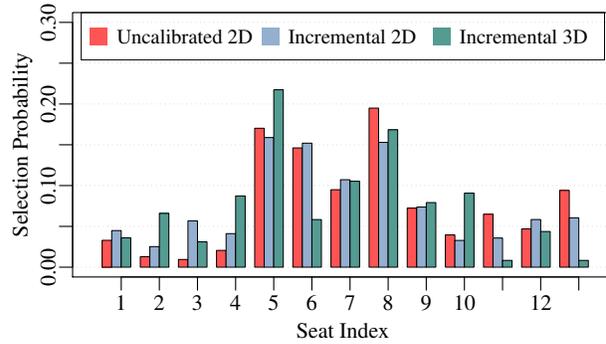Figure 8: Bhattacharyya coefficient of VR and 2D calibration.

Figure 9: Average seat selection probability across all calibration approaches.

and Schatz 2011) could encourage the participants to conduct more iterations so that more reliable data can be collected. Additionally, we assume every passenger to behave the same when in reality the crowd mix might significantly affect the seat occupancy (Schelenz et al. 2012). Some passengers might be more resolute in conquering a seat, other passengers may wish to stand instead of sit, etc. With a large enough test subject set, it is possible to create different profiles based on the observations made in the experiment. These profiles could then be assigned to different agents to reflect a more realistic crowd mix.

The approach we demonstrated in this paper can be considered naive as we neglect psychological rules affecting seat selection altogether and reduce the problem to simple probabilities. For example, some passengers may prefer a window seat or may avoid sitting directly next to someone else if other seats are still available (Berkovich et al. 2013). On top of that, passengers travelling together are more likely to sit next to each other. When asking the participants in our human-in-the-loop simulation why a certain seat choice was made, we observed these rationales, even to the extent that some participants in fact articulated that they choose their seat according to their thermal comfort, i.e., not directly exposed to air conditioning or close to other passengers. Ideally, reducing all these factors to a black box and only considering the resulting seat selection probability would allow us to neglect these complex relations as the final result would inherently include them. To which extent this approach is feasible and which parameters still need to be considered is specific to the application and needs to be evaluated carefully.

Our approach can be applied to calibrate more sophisticated models, however, more holistic data collection is then required, potentially further increasing the number of iterations. In fact, the potential applications of the incremental calibration method include all scenarios where agents affect each other in a feedback loop, e.g., path selection (Shendarkar et al. 2006), Social Force intensity (Kretz et al. 2017), or even acceleration or lane change behaviour in traffic simulation (Brockfeld et al. 2004). Since not all model parameters can be derived directly from observations of a human participant, additional computational steps may be required to determine, e.g., the parameters to the Social Force model required to approximate an observed degree of distance-keeping to the simulated agents. One interesting research direction is the combination of our method with machine learning techniques, e.g., Q-Learning or Neural Networks. The behaviour of an agent would be controlled by a model trained on the observations from previous calibration cycles under the expectation that with each cycle, it reflects the human behaviour more closely. However, the selection of inputs to these models is still challenging and specific to the application.

The main issue certainly is to determine whether the presented approach actually leads to more realistic agent behaviour. With the lack of ground truth data, it is difficult to assess the quality of the calibrated model. The obvious questions whether the output statistics converge to a ground truth value therefore remains unanswered and will be the focus of future work. A ground truth can be obtained in real-world tests using a physical environment with a real vehicle or a mockup, or by analysing video footage.

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7   CONCLUSION

In this article, we presented an approach for the incremental calibration of pedestrian models using human-in-the-loop simulation. We propose to use virtual environments such as a simple 2D graphical user interface or a more sophisticated virtual reality where simulated and human-controlled agents interact. With every calibration cycle, the simulated agents attempt to adopt the previously observed human behaviour, which in turn affects the human participants in their choices, leading to different behaviour compared to experiments with agents that behave according to fixed model parameters. Our method can facilitate the calibration process when the system under evaluation does not (yet) exist or when empirical data is sparse or not available. While the model investigated in our case study is rather simple, our approach can be extended to more complex models and is not limited to output statistics. In future work, we intend to compare the final calibrated model parameters obtained with our approach to a field trial with only human participants. This will allow us to gain better insights in the applicability as well as the limitations of our approach.

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