Data Collection Methods for Agent-Based Crowd Simulation

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Abstract. Real-life data is often used in crowd simulations. This data can be collected using various methods, such as VR, video, device trackers, crowd experiments, or expert knowledge. These methods have different strengths and weaknesses. Currently, no overview exists that clearly outlines these strengths and weaknesses. Furthermore, no existing studies explain which collection methods are best suited for specific modeling applications. This lack of clarity may lead researchers to use methods that do not align with their needs or to set up complex collection methods when simpler ones would suffice. To address this gap, the following question will be answered: What are the appropriate data collection methods and formats for different crowd simulation applications? This study focuses on socio-psychological attributes for specific agent-based models at both micro and meso levels. The findings indicate significant differences between the examined collection methods, with certain methods being more suitable for collecting different types of data. Additionally, there is a clear distinction between methods applied to data-driven versus knowledge-driven models.

Keywords: Crowd simulation · Data collection · Crowd simulation theories.

1 Introduction

Crowd simulation aims to replicate the motion dynamics of individuals in a crowd. The goal is to give insight and/or predict how groups of individuals move and interact with their surroundings (Yang et al., 2020). In recent years crowd simulation has become more prominent, both in academia and in government (Zhong et al., 2022a). Understanding the mechanics of the behavior of crowds has a vast amount of practical applications: determining the best fleeing routes during evacuation (Wong et al., 2017), bottleneck formation during evacuation (Kabalan et al., 2016), predicting pedestrian flows to avoid the clumping of large groups in public spaces (Duives et al., 2013), or even improving visual effects in computer games (Yang et al., 2020).

Regardless of the use case, research into crowd behaviour can be brought back to three goals defined by (Zhong et al., 2022b). It can be used to test scientific theories, formulate design solutions, and generate phenomena that provide insights for further theoretical exploration. Despite this, crowd simulation is a complex research field. The focus of the modeller is usually split between physical aspects, social factors and psychological factors. In addition to this, path planning behaviour and collision avoidance also need to be taken into account (Zhong et al., 2022a).

Crowd simulation can be approached in two distinct ways: knowledge-driven and data-driven modelling. According to (Keller & Hu, 2019), knowledge-driven models rely on expert knowledge as input, which in the case of crowd simulation means interviews with psychologists and social theories (Fridman & Kaminka, 2010). Path planning behaviour and collision avoidance models calibrated on existing data can also be used. A critical disadvantage of this approach may be that the model is biased by the modeler's view. Data-driven models use only observed data as input for the model (Keller & Hu, 2019), reducing the risk of modeling bias. It is possible to look at the data types of crowd simulation using two different perspectives.

The first perspective of Yang et al. (2020) focuses on micro, meso and macro level. Microscopic models focus on the individual behaviour of people in a crowd. The low-level behaviour of the individual is modelled using bottom up modelling techniques, for instance using Agent-Based Modelling (ABM). Dynamic group behaviour in crowd is modelled by mesoscopic models. Lastly, macroscopic models are based on the behaviour of the whole crowd, which is often modelled using fluid dynamics (Yang et al., 2020).

The rest of this paper will be scoped on behaviour models, and therefore Agent-Based Models (ABM) will be used. Accordingly, the focus will be on microscopic models and intra-group relations. Despite this focus, it is still required to take data types of the second school of thought into account: physical, psychological and social data.

The second perspective of Duives et al. (2013) distinguished three types of data that are required for crowd simulation: physical, psychological and social psychological data. Physical data defines objects like doors, walls, chairs and tables. Psychological data focuses on the individual's thoughts and emotions.

Social psychological data differs from psychological data, as it solely focuses on how multiple individuals interact and perceive each other (Duives et al., 2013).

The main challenge of constructing an effective data-driven crowd simulation model lies in creating datasets including all possible scenarios. If the coverage of the scenario space is not adequate, the model will be unable to generate results (Lin et al., 2024). It should be noted that nearly all data-driven models use predefined data for social and psychological data; some do not even consider these aspects, limiting their analysis to collision avoidance methods. Therefore, it is crucial that there is reliable input data of good quality available (Wang & Wainer, 2014).

The quality and structure of the data strongly depends on how the data is collected. Arias et al. (2022) compared collecting data using various Virtual setups and crowd experiments. Furthermore various collection methods deduce similar data. Walking trajectories are, for example, collected using virtual reality (Olivier et al., 2014) , videos (Kim et al., 2016), Bluetooth (Elsayed et al., 2023) and GPS (Toledo Diaz et al., 2018). No good overview exist to indicate which collection method is suitable for measuring data required for crowd simulations. This could lead to researching deciding on an collection method while another is more suitable or more affordable for the use case.

To ensure that the right collection method is used for the right purpose in crowd simulation, this paper aims to address the following research question: What are the appropriate data collection methods and formats for different crowd simulation applications? To achieve this goal, an overview of different data formats and their possible applications is provided. Guidelines to help identify the best data format for the desired modelling approach are also laid out.

The rest of this paper is structured as follows: section 2 provides an explanation of the methodology behind the literature review. Section 3 describes different model paradigms and commonly used model components for crowd simulation. The data collection methods used to gather data are described in section 4. Section 5 discusses the findings of the literature review.

2 Methodology

A literature review on crowd simulation is conducted, based on the four phases described by (Snyder, 2019): designing the review, conducting the review, analysis and writing. These were conducted sequentially.

First, to be able to design the literature review, the authors read four papers (McKenzie et al., 2008; Park et al., 2012; Shendarkar et al., 2008; Zhou et al., 2010) in order to acquire a basic understanding of crowd simulation. The premise of this paper was inspired by this initial reading, namely to create an overview of the current data formats which are available for crowd simulation and how they can be used for different applications. Additionally, the initial search led to key words that supplemented the earliest searches as outlined in the next paragraph.

The online literature review was conducted using Google Scholar and Scopus. It was structured via key words. Search queries were formulated by combining a keyword indicating the domain of crowd behaviour modeling with a keyword specifying a technique/topic. Initially these topics were relatively generic in order to find the techniques that are used, whereas later in the search process the topics were specific theories that were found in earlier searches. An overview of the keywords can be found in Table 1. In this table the keywords are ordered chronologically to when they were searched for as far as is possible, given that the authors conducted independent searches in parallel. In addition to the search using Google Scholar and Scopus, snowballing was performed. This led to the addition of 8 papers.

Table 1: Overview of keywords used

Domain	Technique/Topic
Crowd Simulation	Input data
Data collection	Psychology
Evacuation simulation	Data
Crowd analysis	Behavior theories
Input data	Applications
	Data quality videos
	Belief desire intention
	Proxemics metrics
	Virtual reality
	Data-driven
	Knowledge-driven
	Video analysis
	Evacuation
	Bottlenecks
	Luggage
	Social attachment theory
	Bluetooth
	WiFi
	Social force model
	Group leadership
	Crowd experiment

Results from this search were filtered based on their relevance to crowd simulation data and their quality. The quality check was performed using Scimago by checking their Quartile. If the Quartile was not available, the H-index was taken into account. Q1 and Q2 articles were preferred, and H-indexes of 50 or higher. If papers were deemed relevant, they were added to a spreadsheet overview including their themes and publishers to keep everything well documented. This allowed us to create the overviews of model paradigms, components and their collection methods, which will be shown in the following chapters.

3 Model paradigms and its components

Yang et al. (2020) defined the micro, meso and macro level on which crowds can me simulated. On the meso and macro level the Agent-Based Modeling (ABM) paradigm is the most commonly used approached. For the macro level Fluid dynamics-based models are used. Fluid dynamics-based models are able to capture the particle-like behavior of humans in crowds; however, they are for the most part incapable of representing the complexity that comes with individual decisions. The focus is mostly on the movement of the crowd at large, rather than the behavioral elements that motivate individual choices. Given this, the paper will delve more in depth into the ABM side of modeling approaches.

In the this paper, the collection methods for social psychological and psychological data will be included. Since crowd models on macro levels do not include social psychological and psychological the focus will on ABM models for the micro and meso level.

Following the description of Zhou et al. (2010) an ABM model is a set of autonomous agents which can interact with each other. Each agents has their own attributes which make up their state. Per time tick agents will get the chance to interact in an predefined order. ABM is the most flexible approach since it provides the freedom to include various behavioral details. Additionally, it allows the researcher to use structural decomposition's to decompose components which directly represent parts of the real world (Hofmann, 2004). An ABM often specifies the environment in which the agents interact. An environment can simulated using graphs, grids or continuous space both in two or three dimensions.

When a crowd simulation is simplified it has only two parts. First part, determines the goal of the agent. The goal is often a location to which the agent needs to get. Second part describes the movement of the agent and how the movement is adapted based on its surroundings. Various model define these parts in different levels of complexities and extend. Below different model components will be examined which fulfill these parts. Table 2 gives an overview of which components were used in which papers. Furthermore, it is given which type of data is used as input for the component and what the purpose was of the ABM model which contains the component. This makes it already possible to see which component can be used when. It must be noted that this mostly focus on the movement part since most models use predefined goals to which agents move.

Velocity Obstacle: Velocity Obstacle models are used to generate collision avoiding behavior. Each agent in a simulation has a Velocity Obstacle, a set of velocities that will cause a collision with other agents, assuming their velocities remain constant. By picking a velocity outside of said set, collisions are guaranteed to not happen. According to Park et al. (2012), Velocity Obstacle models do not provide support for group-based movement; velocity matching between group members must be implemented to model behavior like walking together.

Reciprocal Velocity Obstacle: Reciprocal Velocity Obstacle models represent an extension of the Velocity Obstacle paradigm. As stated in van den Berg et al. (2008), reactions in agents limited to immediate obstacles may lead to oscillation in trajectories, affecting the reality of the simulation. To account for

Table 2: Studies and their use of model components, data levels, and simulation purposes

Researchers	Model components	Data level	Simulation purpose
(Park et al., 2012)	Velocity obstacle, Common Ground Theory	Individual	Pedestrian
(Sujeong,2020	Reciprocal velocity obstacle	Crowd	Pedestrian, Evacuation
(Olivier et al,2014)	Reciprocal velocity obstacle 2	Individual	Pedestrian
(Zhang et al., 2022)	Crowd Density-based Reciprocal Velocity Obstacle	Individual	Evacuation
(Kim et al., 2012)	General adaptation syndrome	Individual	Evacuation
(Fridman & Kaminka, 2010)	Social comparison theory	Individual	Pedestrian
(Xie et al., 2021)	Social force model, leadership	Individual	Evacuation
(Aubé & Shield, 2004) (Ivo et al., 2021)	Leadership	Individual	Evacuation
(Shendarkar et al, 2008)	Belief, desire, intention theory	Individual	Evacuation
(Dickinson et al, 2019)	Social Force Model	Individual	Pedestrian
(Dupre et al, 2019)	Social Force Model	crowd	Pedestrian

this, Reciprocal Velocity Obstacle models make each agent aware not only of its potential collisions, but also how other agents may react to their own potential collisions. This is done by choosing the new velocity for an agent as the average between the current velocity and a velocity outside the VO set. In the study by Kim et al. (2016), reciprocal velocity obstacle is extended through data-driven methods. Several experiments and observations are carried out to gather data used for the calibration of the simulation models; above all else, focus is on trajectories. Relevant attributes of these include movement patterns, entry and exit points, and crowd densities in different areas.

Reciprocal velocity obstacle 2: Reciprocal Velocity Obstacle 2 models are a further extension of reciprocal velocity obstacle models. Reciprocal velocity obstacle 2 includes new parameters, such as comfort speed, neighbor distance, radius, and time horizon (considering future collisions) (Wolinski et al. (2014)). These contribute to better collision avoidance and smoother agent trajectories. In the paper by Wolinski et al. (2014), reciprocal velocity obstacle 2 models are part of the models evaluated through a novel framework focusing on the optimization of their parameters based on real-world crowd behavior. Additionally, different distance norms (close within the same group, distance between different groups) are well represented by reciprocal velocity obstacle 2. It should be noted that the reciprocal velocity obstacle 2's advantage is conditional to the size of the simulation, decreasing significantly with higher number of agents.

Crowd density reciprocal velocity obstacle: In real world scenarios, crowd density plays a crucial role in determining the right speed and the shortest path to evacuation. Zhang et al. (2022a) propose an extension of traditional Reciprocal velocity obstacle models based on the density property of crowds. This approach requires precise parameter configuration: data on the position of individuals in experiments was gathered using Raspberry Pis equipped with WiFi network cards and infrared sensors. Crowd density reciprocal velocity obstacle models are based on an algorithm that updates individual agents' velocity at every instant of the simulation. The formula for calculating this updated speed is dependent on the density of the crowd around the agent at that specific instant.Crowd density reciprocal velocity obstacle models represent an improvement on traditional Reciprocal velocity obstacle models in that they avoid congestion on a specific safe exit, allowing for shorter evacuation times and less pressure on a single safe exit.

General adaptation syndrome: According to Kim et al. (2012) , General Adaptation Syndrome (GAS) can be used to simulate behaviour under stress. Therefore, this can be used for evacuation models. The theory distinguishes three phases. In the first phase, the alarm phase, the fight or flight response is activated. As a result, it is tried to mitigate the stress in the second phase. However, when this is not working, the exhaustion phase is reached. To implement GAS in an ABM, Kim et al. (2012) gave the agents a perceived level of stress, maximum stress changing rate and maximum amount of stress. Furthermore, the aggressiveness and impulsiveness of the agent are changed based on the stress levels. Stressors (factors which cause stress) are implemented in the ABM, for instance a fire starts in the office, and it is seen how the agents react to this (Kim et al., 2012).

Social comparison theory: Social comparison theory is based on the fact that humans compare their capabilities with others, if they lack objective means themselves. When the others are more similar to them, or the stronger the connection to the group, the comparison is increased. When differences are detected, individuals will try to decrease them by correcting themselves (Fridman & Kaminka, 2010). Furthermore, Fridman and Kaminka (2010) implemented the social comparison theory in an ABM. For each agent, it was calculated how different they were compared to others. Based on the level of similarity, the agent tried to correct their actions on the selected features. For instance, when an agent is walking in the same direction as the agents around them, the agent will compare itself based on different features, such walking directions, walking speed, and distance between other agents. When they recognize they are walking faster than others, they will change their speed (Fridman & Kaminka, 2010).

Common ground theory: When using common ground theory for crowd simulation, Park et al. (2012) established that actions of agents may be coordinated when they have the same activity. It is important that the agents know that they have a common ground, and that they know that other agents know about the common ground. For example: when people walk in a group through a shopping mall, and they know that they are all looking for the exit, they will follow each other. An advantage of this approach, according to Park et al. (2012), is that it is possible to implement sub goals, for instance visiting the restroom or getting something to eat. There is an initiator and its respondents, three types of navigation between them was implemented. At first lead-and-follow, where the respondents follow an initiator to the sub-goal of the initiator. A second type is divide and proceed, where the initiator follows a sub-goal, and the respondents ignore the sub goal of the initiator and continue towards the main goal. A third type is divide and wait, where the respondents wait for the initiator to finish the sub-goal, and later continue as a group to the main goal. Between the initiator and respondents, it is possible to coordinate non-verbal (for instance using visual gestures or doing actions) or verbal (Park et al., 2012).

Leadership: Some ABM are based on the concept of leadership. For instance Aubé and Shield (2004) implemented leaders in the simulation, they are agents who know the route to the emergency exit. The leader walks to a large group of agents and tries to take them with them to the nearest exit. If an agent does not know the route to the emergency exit, it looks for a large group/leader and will follow them. Ivo et al. (2021) had approximately the same approach, and distinguished between four types of agents: leaders, followers, subleaders and autonomous members. Leader follow behaviour can also be combined with SFM, for example as Xie et al. (2022).

Belief-Desire-Intention: The Belief-Desire-Intention model simulates decision-making in intelligent agents through a representation of their mental process in 3 steps. Beliefs embody what each agent knows about its surroundings; this knowledge can be incomplete and/or incorrect. Desires are the goals of the agent: in a crowd simulation case, this could be reaching safety. Intentions determine the plan(s) agents formulate to achieve said desires. In Shendarkar et al. (2008), the Belief-Desire-Intention model is extended through Virtual Reality experiments with human participants. Shendarkar et al. (2008) examined the decision-making process of subjects when choosing a route to exit from a terrorist threat. Here, the Belief-Desire-Intention model is used to assess how subjects valued the amount of fire, the number of other people, the number of policemen, and the proximity of exits. The paper indicated which of these four aspects were most important in the decision-making process of the subjects and what their preferred choices for pathing to an exit were.

The behavior of these subjects in relation to various factors was captured and used to simulate crowd evacuations. Population numbers were found to be the most relevant when analyzing the magnitude of the simulation's response. The number of exits was also a relevant factor, in correlation to the human-observed behavior of choosing a path based on the visibility of an exit sign.

Social Force Models: Social Force Models apply the concept of social fields to the description of pedestrian behavior. Helbing and Molnár (1995) state that pedestrian routing is characterized by standard stimuli and predictable reactions, which allow for the formalization of pedestrian behavior as an equation of motion. Speed and acceleration of the pedestrian are thus linked with the vectorial notion of a social force, which influences each agent's movement as if they were particles. In Dickinson et al. (2019), the concept of Social Force Models is utilized to explore how density in simulated crowds affects user experience and behavior in virtual reality. The results show that users experience difficulties in navigating virtual crowds when density is increased. Some of the test subjects mention feelings of claustrophobia and perceived rudeness from crowd agents, although this last point may be an artifact of the simulation setting, especially considering the lack of verbal communication.

4 Data collection methods

To create models using the different model paradigms, it is required to collect input data. As mentioned by Duives et al. (2013), three types of data are needed for a successful crowd simulation: psychological, social and physical data. To retrieve this data, there are various collection methods. Below is an overview of the data collection methods mentioned by literature, and the data they collect.

Videos: Videos are used to gathered data of crowds walking through a space. Cameras can be used to gather images or videos and can be combined in a multi camera setup to gather data from multiple angles. In this paper only mono camera setups are examined due the lack of studies using multi camera setups and the indifference of data that is collected. Similarly image analyses are also not taken into account. The quality of the videos is important for extraction data. However, since all the studies succeeded in extracting the desired data from the data this is not discussed further.

Video data can be used to determine walking trajectories, in evacuation and pedestrian situations. Walking trajectories can be used to train a model for the crowd behaviour, for instance while combining with Social Force Model or Reciprocal Velocity Obstacle. Furthermore, video data can be used to derive the background and get an overview of the environment. The background is derived by using a mean or median filter on the all the image of videos. This results an image where all pedestrians are removed. This image is then processed to get the environment. The data-driven approach makes it easier to examine different environments with different crowd densities '(Zhong et al., 2016).

Virtual reality Virtual reality aims to create a virtual environment using computer graphics that users can experience as if it were a real-world (Bowman & McMahan, 2007). The primary methods to indulge users in a virtual environment are Cave Automatic Virtual Environment (CAVE) and Head Mounted Display (HMD). Shendarkar et al. (2008) and Olivier et al. (2014) make use of the CAVE system. Here they surround the user with screens on which the surrounding is projected. The user can navigate through the surrounding with a controller. HMD projects the surroundings using an headset which covers the full eye sight of the user, in combination with a similar controller as CAVE. The study of Arias et al. (2022) determined that a HMD setup more accurately mimics behaviour during an evacuation drill then CAVE. The realism of an virtual environment itself does, however , not influence behavior significantly (van Gisbergen et al., 2019).

Data collected for simulation with virtual reality is mostly about walking trajectories or routes. Here the distinction is made between paths and trajectories. Trajectories define the exact location, velocity at a certain timestamp. Defines on the location the user visited. Virtual reality lends itself well by analysing how the user perceives and interact with its physical environment. Additionally, Olivier et al. (2014), Yin et al. (2022) and Dickinson et al. (2019) showed that virtual reality is great method to measure proxemics. Proxemics analyses personal space and the degree of separation that individuals. Besides physical perception virtual reality is also used to see how individuals perceive dangers in their surroundings and react on them. The study of Shendarkar et al. (2008) and Li et al. (2017) exposes their users to earthquake or fires in the street and then see how the users react. Shendarkar et al. (2008) measured the different attributes on the roads of the users path and from that data derived what type of elements are important for individuals during an evaction for choosing for a fleeing path.

GPS: Toledo Diaz et al. (2018) collected GPS data of pedestrians in cities. Based on the GPS locations and timestamps, it was possible to describe the walking routes individuals will take through the city. The agent can follow one of the routes. To make sure each agent is different in the eventual ABM, each agent had for instance different maximum speeds, vision ranges and perceptions regarding walking fast or slow (Toledo Diaz et al., 2018).

Bluetooth : According to Elsayed et al. (2023), Bluetooth Low Energy (BLE) is part of Bluetooth 4.0, and does not consume much energy. Therefore, it can be possible to place Bluetooth beacons, which use BLE, in a building, and connected them to the devices of visitors. Based on the connection, the distance between the Bluetooth beacon and person could be estimated. BLE is accurate ranging from 0.9 to 2m. The location points are then implemented in the agent based simulation.

Based on the locations, Elsayed et al. (2023) distinguished different walking paths into a building during evacuation. It is possible to simulate the agents walking different routes through the building to the exit, and the optimal path may be found. Furthermore, it can help creating signs to guide visitors to the emergency exit while evacuating. For example, at the start, most people will be guided to the left to use the left emergency exit, but after a few minutes, it may become busy there, and the sign will lead to another emergency exit. That way, the crowd will be distributed over the different exits (Elsayed et al., 2023).

WiFi: Researchers Zhang et al. (2022b) connected a wireless WiFi network card and infrared sensor with Raspberry Pi. The Raspberry Pi detects the WiFi signal of the smartphone in the area. The Raspberry Pi also detects the sensor mode, to establish the exact time someone passed the point. The agent moves to the safe area, where another Raspberry Pi detects the WiFi signal and sensor data to establish the arrival time. Based on this, the evacuation time and speed can be determined. To optimize the evacuation trajectory, Crowd density reciprocal velocity obstacle was used to consider the effect of crowds on the speed (Zhang et al., 2022b).

Crowd experiments: Crowd experiments can be useful input for crowd simulation, for example Fridman and Kaminka (2010) used existing crowd simulation data of Daamen and Hoogendoorn (2003) about walking lanes of pedestrians. While conducting a crowd experiment, various data types can be derived. For instance during Xie et al. (2020), the participants were involved in a room evacuation. They are all wearing a coloured helmet, and a video camera can be used to analyse the behaviour and movements of the individuals. It is important to mention that crowd experiments should therefore be combined with another data collection method to retrieve the data. For instance GPS, Bluetooth, WiFi or video can be used. Different questions can be answered using crowd experiments, for example: what is the effect of groups on crowd simulation, how do the participants move, and what is the average evacuation time (von Krüchten & Schadschneider, 2017; Xie et al., 2020, 2021).

Expert knowledge: Lastly, it should be mentioned that some theory based crowd simulation models do not state they use extra data beside the social theory Xie et al. (2022). Social theories are based on expert knowledge of sociologists and psychologists, and it is hard to determine what this knowledge is based on. Therefore, the data collection method for these models is set on "expert knowledge". For example based on the General Adaptation Theory, Kim et al. (2012) examined agent behaviour in stress situations. When running an ABM while using General Adaptation Theory, insights will be given on agent behaviour in stressful situations. How much does their walking speed increase, do they become selfish and reckless, or are they helping others? This is all depending on the level of stress caused by the scenario (Kim et al., 2012).

Furthermore, social comparison theory gives insights into pedestrian movements. During the study of Fridman and Kaminka (2010), Different types of pedestrian movements can be identified: how do pedestrians move as individuals and how do individuals move when their surroundings are different. Furthermore, the movement of pedestrians in groups can be identified, and their behaviour when there are for instance obstacles on the sidewalk.

5 Discussion

In this and the upcoming sections, the shortcomings and challenges will be discussed. First, the focus will be on some of the overarching problems and challenges related to the different model paradigms and data collection methods for crowd simulation. Furthermore, a new distinction will be made for the different data types. The second part will focus on an overview table, which compares the different collection methods and determines their appropriateness for achieving the crowd simulation goals. Lastly, limitations will be mentioned and the research question will be answered.

5.1 Model paradigms

In the following, we distinguish three categories of model components: velocity obstacle models, group behavior models, and social force models. Velocity obstacle models mainly focus on collision avoidance, using algorithms to determine velocities and trajectories of agents in real-time. Group behavior models investigate the interactions between individuals within a crowd; social force models borrows concepts and notions from theoretical physics, modeling them onto crowds and individuals. Gathering the data necessary for simulation calibration is an expensive and complex endeavor, representing the key challenge across all model paradigms. The data-driven approaches, especially velocity obstacle and social force models, require detailed information on individuals' trajectories, social interactions, and reaction to their surroundings. Due to the focus on velocities for each agent, velocity obstacle models require thoroughly specific motion and position data; on the other hand, social force models need psychological and social interaction data, which makes the collection of large-scale data challenging and expensive. Similarly, group behavior models may face difficulties in capturing cognitive and leadership dynamics accurately in large groups. These last two groups also require the support of behavioral theories for individual crowds, and an effort to transpose their notions and ideas into simulation components.

5.2 Data Collection Methods

When looking at the different data collection methods, Virtual Reality is the least suitable for large datasets. Virtual Reality is precise, but can only measure the walking trajectories and paths of one individual, while video can do multiple simultaneously. However, this does make Virtual Reality precize. With Virtual Reality, researchers have full control over the sensors used to measure behavior and the virtual environment in which the subjects act. Collection methods like video, Bluetooth, WiFi, and GPS lack this level of control and accuracy. Another shortcoming of Virtual Reality may be that there is no dynamic interaction between the simulated agents and the user. The lack of interaction makes it difficult to collect data on social perception. However, since dynamic interactions with physical surroundings are less important, Virtual Reality is still suitable for measuring physical surrounding perception, as demonstrated in the studies by in the studies by Shendarkar et al. (2008) and Li et al. (2017).

Video, Bluetooth, WiFi, and GPS can be distinguished based on their accuracy and coverage. Of these, video is the most accurate method. The main reason is that cameras can capture the person directly, whereas the other methods require individuals to wear devices emitting signals. The signals are less precise than the camera, for instance Bluetooth is accurate for 0.9-2 meters (Elsayed et al., 2023). However, the video data is limited to the view of the camera, while Bluetooth, WiFi and GPS can cover large areas.

Another data collection method is crowd experiments. The advantage of crowd experiments is that it makes it possible to simulate the real world with humans, while monitoring exactly what they are doing. However, crowd simulation does have various disadvantages. At first, crowd experiments are very complex and costly due to their large scale. Furthermore, it is difficult to analyze these experiments to receive the numerical data Fridman and Kaminka (2010). Another data collection method, for instance video or a device tracking method, is required to analyze the data. Moreover, Yang et al. (2020) stated that the scene used for crowd experiments is often too simplistic, therefore does not reflect the real-world. Lastly, if participants of the simulation may know that it is an experiment, they behavior may be different than during an emergence Yang et al. (2020).

Lastly, models are often based on expert knowledge. The model is based on a certain theory, for instance General Adaptation Syndrome or Social Comparison Theory (Fridman & Kaminka, 2010; Kim et al., 2012). The main problem is that theories can be interpreted in different ways, and it is possible that the implementation of the theory is not correct. Therefore, the model will be incorrect too. Furthermore, it is hard to implement theories in ABM.

When looking at the reproducibility of these methods, video and the device tracking methods are the easiest. They collect the data and the algorithm will receive the correct data types. The device tracking methods are not very precise, and therefore small errors will not be the problem. Reproducibility in Virtual Reality is challenging due to human-computer interaction. If researchers want to validate their results, they must ensure the validity, which is impossible because the participants can never be the same as the hardware (Hepperle et al., 2021).

5.3 Data Types

Although using the data division of Duives et al. (2013) into social, psychological, and physical data is an effective way to describe crowd simulation input data, it is not well suited for characterizing the output data from collection methods. Collection methods for example can capture walking behaviour differently as trajectories where the position is indicated with time or paths which only focus on location. The distinction of Duives et al. (2013) is not able to capture these details. So, in this paper another division is proposed. This division is designed to make it easier to explain differences in all output data for crowd simulation.

Walking trajectory describes the positions of a person at a certain time over a duration between the beginning and the end point. If the time at which the position is measured is notated as T. A walking trajectory can be written down as $W_{traj} = \{(t_1, p_1), (t_2, p_2), (t_3, p_3), (t_n, p_n) \mid t \in T, p \in S\}$ where $T \subseteq R$ is a set which contains all the times stamps add which a measurement is stored. $S \subseteq R^2$ contains all the coordinates of the space where the measured subject can go. Due the incorporation of time it becomes possible to calculates the subjects acceleration and velocity. Incorporating this will lead to the notation as follows $W_{traj} = \{(t, p, v, a) \mid t \in T, p \in S, v \in V, a \in A\}$ with $V \subseteq R^2$ and $A \subseteq R^2$. Often data stores multiple path so dataset of trajectories like $D_{traj} = \{W_1, W_2, W_3, W_3, W_n\}$.

Walking paths differ from walking trajectories in that there is no time indication for the position of the measured subjects. So walking paths are just $W_{path} = \{p \mid p \in S\}$. The study of Shendarkar et al. (2008) uses the walking paths for graph theory where edges were created between points. The edges were labelled with data describing the characteristics of that path. For example, the level of fire on the road that the edge represents. If a graph $G = (V, E)$ where V are the vertices $V = \{p_1, p_2, p_3, p_n\}$ and the edges $E = \{(p_1, p_2, f_{fire}), (p_n, p_n, f_{fire}) \mid p \in V, f \in F\}$ where $F = [0, 1]$. The W_{path} would be $G' = (V, E)$ which is $G' \subseteq G$. It must be noted that the time is available the for the starting point/vertices and ending point/vertices. So p_1 and p_n have a $t_1$and t_n.

Physical Surrounding perception defines how the subject perceives its surrounding. Here surroundings include only physical phenomena. For example, Shendarkar et al. (2008) measures the perception of fire, crowd, policemen and exits on a certain road during an evacuation. Li et al. (2017) measured the perception of dangers objects in the surroundings and how the subjects then interacts with the objects during an earthquake. Li et al. (2017) associates perception with an event, an earthquake, with a certain time duration, while Shendarkar et al. (2008) associates perception of space. An example of how perception of space could be formulated is given in the above paragraph about walking paths. An formulation that accommodates both is $P = \{(l_1, t_1, (s_{11}, s_{12}, s_{1n})), (l_m, t_m, (s_{m1}, s_{m2}, s_{mn}))\}$. Here l is associate with a spatial space which could be a location, street, room, etc. s is what is perceived by the subject. With Shendarkar et al. (2008) s is the perception of fire and with Li et al. (2017) it could be the perceived danger of an vase, chair or closet.

Social Surrounding perception is similar to how the physical surroundings perception is defined. The major difference is that instead of l which associated with a location there is k which is associate with a agent in the vicinity of the subject. s is then perception of a certain agent. Xie et al. (2022) used leader–follower behaviour in his model. Here a subject is evacuating and looks to the agents that are in front of them. For all these agents a value is calculated how much this agent influences the behaviour of the subject. moreover, if the value is high enough the agent will be recognised as leader. Here, for every agent their are values for s_1 and s_2. s_1 the influence on behaviour between $[0, 1]$ and s_2 indicating if agent is seen as a leader which is binary.

Agent characteristics are all the relevant characteristics corresponding to the subject. The Agent characteristics is the set of characteristics $X = \{x_1, x_2, x_n\}$. Here X is an representation of the state variables of the subject. These characteristics can, for example, indicate simple demographic data or psychological data. For psychological data, like stress, it is important to include time since stress can change over time. Including time the set of s becomes $X = \{(t_1, (s_1 * a_1, s_1 * a_2, s_n * a_n)\}$.

Comparing the three data types of Duives et al. (2013) to the proposed types, the social surrounding perception is similar to social psychological data, physical perception data is similar to psychological data and Agent characteristics is similar to psychological data. Physical surrounding perception is added since it can be used to describe somebodies association with a physical object. This has an physical component (physical object) and psychological component (attitude towards object). Walking trajectories and path are hard to place within the Duives et al. (2013) data types. They are added since a lot of collection methods focus on capturing these types and then a lot studies use them to train their models with.

Table 3: Overview of the combination of data types and the collection methods and the characteristic of these pairs.

Data type	Collection method	Suitable for	Purpose	Driven approach	Collected in
Walking trajectory	Virtual reality	Velocity Obstacle, Social force model	Pedestrian, Evacuation	Knowledge-driven	(Olivier et al,2014) (Dickinson et al, 2019)
	Video	Reciprocal Velocity Obstacle, Social force model	Pedestrian, Evacuation	Knowledge-driven, Data-driven	(Sujeong,2020) (Kang Hoon) (Dupre et al, 2019)
	Bluetooth	ABM*	Evacuation	Data-driven	(Elsayed et al., 2023)
	WiFi (Raspberry Pi)	Reciprocal Velocity Obstacle	Evacuation	Data-driven	(Zhang et al., 2022)
	GPS	ABM*	Pedestrian	Data-driven	(Diaz et al., 2018)
Walking path	Bluetooth	ABM*	Evacuation	Data-driven	(Elsayed et al., 2023)
	WiFi (Raspberry Pi)	Reciprocal Velocity Obstacle	Evacuation	Data-driven	(Zhang et al., 2022)
	GPS	ABM*	Pedestrian	Data-driven	(Diaz et al., 2018)
Physical surrounding perception	VR	Believe, desire, intention theory	Evacuation	Knowledge-driven	(Shendarkar et al, 2008)
Social surrounding perception	Crowd experiments	Social comparison theory	Pedestrian	Knowledge-driven	(Fridman & Kaminka, 2010)
	Expert knowledge	Common Ground Theory, Velocity Obstacle	Pedestrian	Knowledge-driven	(Park et al., 2012)
		Leadership theories, Social force model	Evacuation	Knowledge-driven	(Xie et al., 2022) (Aubé & Shield, 2004) (Ivo et al., 2021)
	Virtual reality	Believe, desire, intention theory	Evacuation	Knowledge-driven	(Shendarkar et al, 2008)
Agent characteristics	Virtual reality	Believe, desire, intention theory	Evacuation	Knowledge-driven	(Shendarkar et al, 2008)
	Expert knowledge	General adaptation syndrome	Evacuation	Knowledge-driven	(Kim et al., 2012)

5.4 Data Methods

Walking trajectories and walking paths use the same data collection methods, with the difference being that walking trajectories account for the time dimension. If higher precision is required, walking trajectories are preferred. However, if time-specific data is not needed, walking paths are sufficient, as they require less data to process.

Walking trajectories and walking paths are modeled using techniques such as Social Force Models and Reciprocal Velocity Obstacles. It is interesting that social theories are rarely used while measuring walking trajectories and paths. This is due to the fact that models such as social comparison theory, leadership theories, and common ground theory require a predefined walking path for a group of agents, and focus on how other agents respond to it. Furthermore, these theories cannot directly determine walking paths or trajectories, they can only estimate walking speeds.

Crowd experiments are similar to Virtual Reality. Virtual Reality is widely used because it allows the collection of all the different data types. However, crowd experiments are only used to study social surroundings and perception. This could be because crowd experiments typically require additional data collection methods to collect the data of the experiment, while Virtual Reality is more straightforward to use. Despite this, crowd experiments could be favorable when creating larger models, where Virtual Reality may be less suitable due to its limitations in handling the behavior of multiple subjects simultaneously.

Social surrounding perception does not use tracking methods such as GPS, Bluetooth, and WiFi. Social surrounding perception aims to track how the behavior of other agents influences a subject, which cannot be achieved through data tracking alone. As such, these tracking methods are not recommended for this purpose.

Agent characteristics, on the other hand, are only captured by General Adaptation Syndrome. Other social theories, such as common ground, leadership dynamics, and Social Comparison Theory, focus primarily on how agents adapt to the behavior of others, but they do not account for individual personalities, making them unsuitable for this purpose.

Finally, Virtual Reality and social theories are knowledge-driven approaches, while methods like video, GPS, Bluetooth, and WiFi are data-driven. If a modeler intends to directly integrate data into the model for training purposes, data-driven methods are recommended.

5.5 Limitations

The aim of the paper was to provide an overview of the currently relevant data formats and how they fit different applications. The literature study and overview have limitations in terms of completeness.For completeness there are two shortcomings. First only ABMs are considered. This make the paper less effective if collection methods are needed to create an model on the meso level. Additionally, models on the micro and macro level which are not ABMs will have a hard time using the overview provided in this paper. Second shortcoming is the number of studied literature. The literature review does not cover all the relevant studies concerning crowd simulation for ABM. This incompleteness could mean that some data collections methods were also applied for certain data types but included here. So the paper can not be used to determine which is not possible. Instead it can conform what is.

5.6 Conclusion

In this paper, an overview of different data formats and their application is presented. Six new categories of data types were established, as the existing categories were found to be insufficient. Additionally, various data collection methods were examined, including Virtual Reality, video, device tracking methods, crowd experiments, and expert knowledge. The study also investigated how these data types align with different modeling paradigms, such as velocity obstacle models, group behavior models, and social force models. All of this information has been presented in Table 2. In response to the research question, "What are the appropriate data collection methods and formats for different crowd simulation applications?", the answer is context dependent. The suitability of data collection methods and formats differs, based on the specific goals, scale, and resources of the simulation.

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