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RESEARCH

Agent-based crowd simulation: an in-depth survey of determining factors for heterogeneous behavior

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Abstract
In recent years, the field of crowd simulation has experienced significant advancements, attributed in part to the improvement of hardware performance, coupled with a notable emphasis on agent-based characteristics. Agent-based simulations stand out as the preferred methodology when researchers seek to model agents with unique behavioral traits and purpose-driven actions, a crucial aspect for simulating diverse and realistic crowd movements. This survey adopts a systematic approach, meticulously delving into the array of factors vital for simulating a heterogeneous microscopic crowd. The emphasis is placed on scrutinizing low-level behavioral details and individual features of virtual agents to capture a nuanced understanding of their interactions. The survey is based on studies published in reputable peer-reviewed journals and conferences. The primary aim of this survey is to present the diverse advancements in the realm of agent-based crowd simulations, with a specific emphasis on the various aspects of agent behavior that researchers take into account when developing crowd simulation models. Additionally, the survey suggests future research directions with the objective of developing new applications that focus on achieving more realistic and efficient crowd simulations.

Keywords Crowd simulation · Autonomous agents · Psychological models · Microscopic models · Multi-agent simulation

1 Introduction

Crowd simulation or modeling has attracted significant attention in recent years due to its potential broad applications. Crowd simulations are integral in diverse contexts such as entertainment, training simulations, and evacuation scenarios, playing a pivotal role in each. As computer technology advances, the exploration and control of human behavior have become prominent areas of study. Investigating how to simulate lifelike individuals holds immense significance for improving the authenticity of visual effects, elevating the immersion in virtual reality, and refining the rationale behind urban planning and the efficiency of emergency evacuation. Despite considerable progress and rapid development in this field, numerous challenges persist, impeding the attainment of realism in crowd simulation.

Modeling a heterogeneous crowd is intricate, involving the interplay of various factors that encapsulate a range of psychological, physiological, emotional, and environmental aspects, making individual behavior intricate in diverse situations. Researchers have initiated efforts to incorporate these factors into crowd simulation, thereby elevating the authenticity of agent behavior in simulated crowds.

This survey thoroughly delves into various factors examined by researchers, intending to model microscopic crowd models that scrutinize low-level behavioral details and individual features of virtual agents. Consequently, macroscopic crowd simulations that focus on agent path planning and collision avoidance with a particle like treatment, as well as mesoscopic/hybrid crowd simulations that combine both microscopic and macroscopic aspects, are intentionally excluded from the scope of this survey. Therefore, the target audience for this survey paper consists of researchers and practitioners interested in microscopic crowd simulation. It aims to highlight diverse advancements in agent-based crowd simulations, particularly emphasizing various aspects of agent behavior that researchers consider when developing crowd simulation models.

We formulated following research questions to systematically delineate the factors influencing virtual crowd sim-

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ulation and identify existing gaps in agent-based crowd simulation research.

– What key factors do researchers prioritize when engaging in the simulation of virtual crowds?
– In the realm of agent-based crowd simulation, what are the present voids or inadequacies in the existing body of research?

2 Related works/surveys

In the field of crowd simulation, various surveys have emerged, with some concentrating on both macroscopic and microscopic models [73, 112, 117, 119], while others predominantly delve into microscopic simulations where agents are attributed with specific properties [106, 117]. Certain studies seek to amalgamate both approaches, giving rise to surveys focused on mesoscopic or hybrid models [46]. However, a notable observation is that most of these models fall short in implementing complex social, physical, and psychological behaviors at the individual level. The survey conducted by Lemonari et al. [57] categorizes crowd simulation components based on factors such as emotion and environment. Yet, it primarily focuses on simulation authoring and control rather than exploring broader aspects of crowd behavior modeling. Other surveys [53] predominantly concentrate on reinforcement learning approaches for simulating virtual crowds, with minimal discussion on various aspects of agent behavior. Primarily, they center on navigation issues, overlooking a broader range of elements that shape crowd dynamics. Nevertheless, only a limited number of surveys specifically address crowd simulations, where the emphasis is placed on modeling agent behavior grounded in the traits of virtual agents and their interactions with the environment. This section aims to discuss some of the previous works on agent behavior modeling.

In the survey conducted by Yang et al. [117], the authors delved into both macroscopic and microscopic crowd simulation models. Notably, they dedicate a subsection to discussing some personality models and emotion contagion theories related to agent behavior. While this survey highlights relevant research papers, its scope is confined to those involving personality and emotional contagion models. However, it is crucial to recognize that agent behavior can be influenced by a myriad of factors beyond personality and emotion, including job role transitions, social dynamics, environmental changes, geometric constraints, and agent physiology. Likewise, there are few surveys that focus on specific factors of agent-based crowd simulations such as environmental factors (evacuation, etc.) [21, 96] and emotion contagion [104]. In [75], there is discussion of a limited number of features characterizing crowd simulation systems, albeit with a notable absence of in-depth exploration on the subject.

Our survey aims to thoroughly explore the influential factors that shape the behavior of virtual agents, thereby influencing the modeling of crowd simulation. While the list of influencing factors is extensive, we focus our discussion on factors that are more popular and commonly incorporated in numerous existing research studies.

3 Materials and methods

3.1 Identification of relevant studies

We systematically collected research work from reputable sources, including Scopus, Google Scholar, IEEE, and ACM, utilizing the following queries: (1) crowd simulation, (2) virtual crowd, (3) agent-based crowd. The concluding literature search was conducted on January 25, 2024. We have meticulously filtered studies, specifically incorporating those that elucidate methods for simulating crowds, encompassing aspects such as navigation, personality, emotion, and other simulation factors.

3.2 Inclusion criteria

We established specific inclusion criteria for the studies considered in this review. These criteria include: (1) publication in a journal, conference proceedings, or dissertation, (2) full presentation in the English language, and (3) explicit mention of at least one of the factors outlined in the survey (e.g., navigation policy, personality and emotion, environmental factors (evacuation and constraints), perceived emotion, group dynamics, physiology, goals, and roles and needs).

3.3 Literature compilation

The selection process followed a structured method. Initially, a pre-selection was conducted by carefully examining the title and abstract of each paper. Studies were excluded if it was evident that they did not present an agent-based model or did not specify any factors listed in the survey (criterion 3).

3.4 Results

Following the search process, we identified 383 different articles. Subsequently, after applying the criteria detailed in Sect. 3.2, 107 articles are finally considered for the survey. As a result, the review covers 27.9 percent of studies that adhere to the specified criteria. Most of the rejections were made according to the criteria outlined in criteria 3 of 3.2.

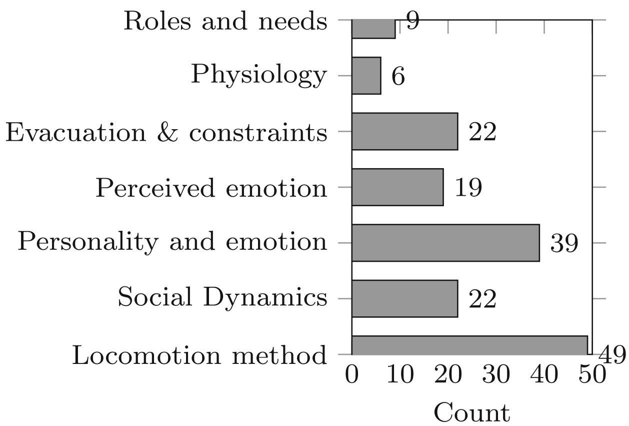

Fig. 1 The considered factors that affect agent behavior. The number on the X-axis shows how many references consider the specific factor

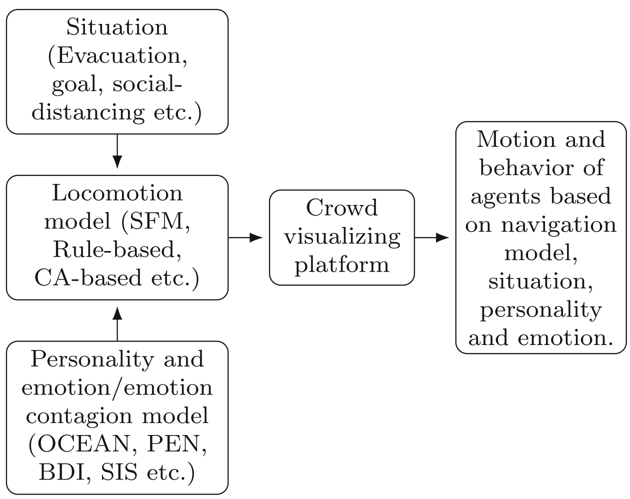

Fig. 2 The diagram illustrates a structured workflow for crowd simulations, where situational parameters such as evacuation and goals inform a locomotion model (SFM, rule-based, etc.). This model is then enhanced by incorporating personality and emotion contagion models such as OCEAN, PEN, BDI, and SIS. The final model then produces crowd simulations that integrate all these dimensions

4 Factors affecting agent behavior

Populations and crowds inherently demonstrate non-uniform behavior, given the diverse characteristics of individuals within them. This variability in behavior stems from a multitude of factors. While the array of influencing factors can be extensive, our focus is specifically on those that wield a substantial impact on agent behavior and enjoy popularity within the research community.

This section aims to elucidate these influential factors. Figure 1 provides a visual representation to illustrate the diverse factors that exert influence on agent behavior. Moreover, the approach outlined in Fig. 2 exemplifies a typical methodology employed by crowd simulation systems.

4.1 Locomotion policies

Locomotion policies play an important role in shaping the behavior of agents in crowd simulations. Most of the research works incorporate at least one type of locomotion policy, often coupled with a few behavioral factors detailed in subsequent sections. Reynolds introduced the pioneering crowd simulation system, “Boids,” in 1987 as an artificial life project aimed at replicating the flocking behavior observed in birds [87]. In this system, agents (boids) possess the ability to perceive and individually react to the environment and other entities within the simulation. Subsequent years have witnessed substantial endeavors focused on improving various facets of crowd simulation, including enhancements in path planning, collision avoidance, and navigation within expansive virtual environments.

Despite the multitude of locomotion models developed in current research, the well-known crowd simulation path planning typically falls into three traditional categories: social force models, rule-based models, and cellular automata (CA) models. These techniques are often classified as microscopic models, where individuals are considered discrete objects whose motions are influenced by their neighbors and obstacles. In this survey, our focus is on understanding agent behavior and the factors that influence these behaviors. Consequently, we exclusively delve into microscopic models. Table 1 presents an expanded categorization of locomotion models.

Numerous crowd simulation methods can find their roots in the empirical social forces model by Helbing and Molnar [43]. This model employs repulsion and tangential forces to represent interactions between individuals and obstacles, resulting in realistic “pushing” behaviors and variable flow rates. Helbing et al. [42] later used this model to investigate panic and jamming caused by uncoordinated motion in crowds, specifically considering the influence of psychological and physical forces on crowd behavior. The social forces model remains the most popular navigation model to date; many researchers use or extend it for their research studies.

On the other hand, rule-based models, exemplified by Reynolds’ pioneering boids system [87, 88], were initially developed to simulate animal behavior, such as flocks, herds, and schools of fish. Each “boid” in this model adheres to behavioral rules that encompass separation, alignment, and cohesion. While widely acknowledged for its simplicity, researchers have made efforts to enhance the original Reynolds model. In the original framework, cohesion and separation serve as complementary steers. However, Hartman and Benes [40] improved the model by introducing a complementary force for alignment, allowing for leadership dynamics to change. This additional steer determines the likelihood of a boid becoming a leader and attempting to escape. Furthermore, Silva et al. [94] introduced a

Table 1 Overview of factors, their types, and corresponding studies. Note that some studies consider more than one factors

Factor	Factor categories	References
Locomotion method	Social Force	[15, 16, 18, 29, 39, 42, 43, 51, 54, 59, 76, 80, 81, 109, 121]
	Rule-based	[31, 44, 61, 62, 82, 87, 88]
	Cellular Automata	[18, 22, 34, 49, 64, 67, 100, 111, 120]
	Velocity-based	[37, 38, 62, 99, 101, 114, 118]
	Vision-based	[28, 45, 63, 70, 77]
	Others	[71, 72, 76, 116]
Personality and emotion	OCEAN	[18, 25–27, 50, 62, 66–68, 111, 113]
	PEN	[30, 38, 99]
	OCC	[25–27, 67, 84]
	ASCRIBE	[13, 14, 68]
	ESCAPES	[14, 102]
	PAD	[25, 69]
	BDI	[24, 93, 99]
	SIS-based	[11, 34, 62, 66, 67, 111, 121]
Environmental factors	Natural disaster	[44, 61, 62, 108]
	Human induced/Artificial disasters	[44, 67, 86, 93, 115]
	Way-finding	[83, 84]
	Evacuation constraints	[15, 16, 37, 39, 42, 80–82, 107]
Perceived emotion	Fear/panic	[27, 42, 47, 67, 80–82, 86, 89, 102, 114, 115, 120]
	Anger/grievance	[31, 35, 44]
	Positive/negative	[31, 115]
	Appraisal theory	[5, 36, 85]
Social Dynamics	Leader-follower	[4, 40, 44, 52, 64, 68, 83–85, 102]
	Grouping behavior	[15, 17, 47, 51, 64, 87, 88, 120]
	Pandemic	[3, 19, 59]
	Other group dynamics	[65, 102]
Roles and needs	Job roles	[60, 92, 95]
	Social roles	[41, 60, 74, 83, 92, 98]
Physiology	Strength, gender, age, etc.	[70, 84, 113, 118]

methodology aimed at incorporating parallelism to enhance the performance of Reynold's Boids model, facilitating the simulation of very large groups.

Cellular automata models, exemplified by these works [22, 49, 100], are well known for their efficiency and straightforward implementation. These models operate by discretizing the floor space, allowing individuals to move only when the adjacent cell is unoccupied. To incorporate higher-level behaviors such as collision avoidance, the paths toward high-level goals can be precomputed and stored within the 2D grid, as demonstrated in [64].

Certain research works [37, 38, 62, 101, 114, 118] leverage geometric formulations grounded in velocity-based models such as velocity obstacle (VO) [33], reciprocal velocity obstacle (RVO) [9], optimal reciprocal collision avoidance (ORCA) [103], and hybrid reciprocal velocity Obstacle (HRVO) [97], to simulate local collision avoidance behavior, considering neighbor information to make optimal decisions and generate emergent crowd phenomena.

Recent research works [56, 79] highlighted the significant potential of reinforcement learning-based models for crowd simulations. Additionally, data-driven approaches combined with ML algorithms [20] have been utilized to create virtual crowds that closely mimic realistic human behavior. However, while these models adeptly address navigational challenges, they fall short in integrating the nuanced aspects of behavior such as personality, psychology, and environmental factors. Hence, our survey does not delve deeply into machine learning contributions within this context.

Other locomotion approaches involve strategies such as the lattice gas model [71, 72], fuzzy-logic-based models [76], vision-based models [28, 45, 63, 70, 77], and game theory models [116]. Fuzzy logic, in particular, provides a suitable framework for integrating imprecision and subjective elements inherent in environmental perception into the perceptual action model. Vision-based models, on the other hand, enable collision avoidance strategies using visual stimuli, as demonstrated in this work [77].

This section underscores the critical importance of locomotion policies in crowd simulation, detailing traditional methods like social forces and rule-based models, as well as modern approaches including vision-based algorithms.

4.2 Personality and emotion

The autonomous and multi-agent system community has been dedicated to placing considerable attention on the modeling of personality, defined as an exclusive combination of behavioral, emotional, temperamental, and mental characteristics that distinguish individuals from each other. The incorporation of these aspects of individual differences is intended to enhance the authenticity of characters by introducing natural variations in behavior. This, in turn, contributes to the overall diversity of behaviors within the simulated crowd as modeled by some studies [51, 83, 84].

The OCEAN personality model [110] and the PEN model [30] have gained good acceptance from the research community to represent personality traits of individuals. The OCEAN model, also known as the Big Five personality traits, includes Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism, to represent certain dimensions of personality. On the other hand, the PEN model [30] contains three major factors which categorize personality into Psychoticism, Extraversion, and Neuroticism. People with different personality traits may perceive and react to crowds in various ways.

While personality is undeniably important, it alone may not be sufficient to determine emergent behavior in specific scenarios. Therefore, some researchers [26, 27], introduced emotion components by leveraging social theories like OCC (Ortony, Clore, and Collins) [78]. The model delineates approximately 22 emotion categories and comprises five essential processes that define the complete system governing the behavior of characters from the initial categorization of an event to the resulting behavior. As an example, the study conducted by Durupinar et al. [27] integrates a personality model grounded in the Ocean model [110] and an emotion model based on OCC [78] to augment the HiDAC (High-Density Autonomous Crowds) system [82]. Moreover, researchers developed personality-to-behavior modeling to establish parameters for behaviors such as leadership, communication proficiency, panic level, pushing, walking speed, and the ability to explore the environment. They used various psychology-based models such as Pleasure-Arousal-Dominance (PAD) [69] to establish consistent mappings to OCC emotions [78] and OCEAN [110] personality traits and to model decision-making aspects such as emotion expression and behavior selection. This approach offers a convenient bridge between these two distinct models.

An additional example is found in the research presented by Allbeck and Badler [1, 6], which explored a parameterized system with the goal of creating more expressive gestures. Their system drew inspiration from various sources, including the OCEAN personality model, the EMOTE system [23], and Laban Movement Analysis (LMA) [8]. The EMOTE system, a 3D character animation approach, integrates Effort and Shape qualities into independently defined underlying movements, resulting in more natural synthetic gestures. In contrast, LMA is a method for observing, describing, notating, and interpreting human movements. Similarly, several other works [38, 51] modeled heterogeneous crowd behavior based on different personality traits. Figure 3 illustrates the categorization of various personality and emotion theories.

This section addresses incorporating personality traits and emotions into crowd simulations to increase authenticity and diversity. It outlines how researchers apply models like OCEAN and PEN, along with emotion theories like OCC, linking personality to decisions and gestures for more realistic simulations.

4.3 Perceived emotion and tension

In addition to their inherent personalities, the way agents perceive their environment and the information they can gather through sensing mechanisms play an important role. It is essential to clarify that personality and emotion, as discussed previously, represent enduring traits and transient states, respectively. In contrast, perceived emotion pertains to individuals' interpretation and response to emotions within their environment.

In 1999, Scherer proposed the appraisal theory [91], which posits that emotions arise from a deeply subjective cognitive process. In this process, individuals evaluate objects, behaviors, and events in their environment relative to their own values, goals, and overall well-being. Several studies [5, 48] have endeavored to incorporate this concept into their research. For example, Kim et al. [48] employed a stress model to simulate dynamic patterns of crowd behavior. They also endeavored to endow an agent with the ability to perceive the situation based on its own characteristics and adapt its behavior accordingly. Another study [89] explored the impact of manipulating agent stress levels on crowd behavior. The objective is to incorporate the notions of stress and comfort into the agents, to study relationship between stress levels and the reaction of crowds Another research study [47] explored the understanding of how people perceive and evaluate emotions when faced with emergencies or external events. It models the evolution of emotions and scrutinizes

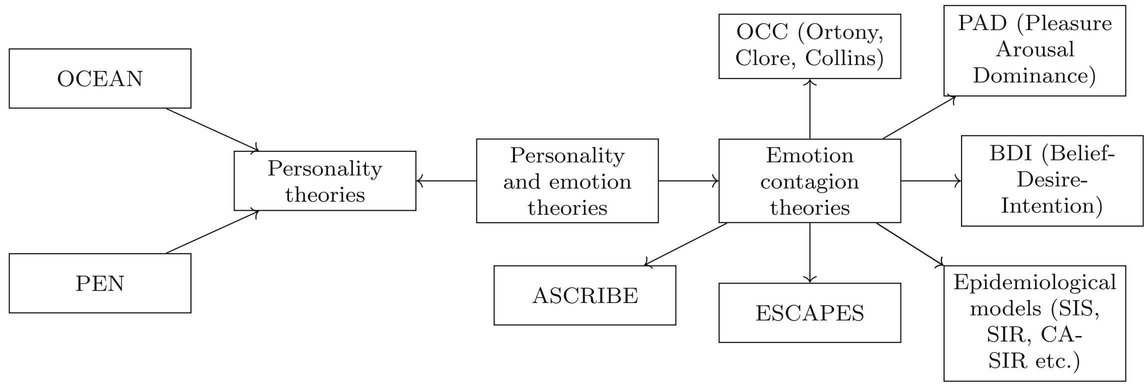

Fig. 3 The diagram represents key personality (OCEAN, PEN) and emotion contagion (OCC, PAD, BDI, ESCAPES, ASCRIBE, SIS, etc.) theories considered by researchers to embed psychological attributes in virtual agents for crowd simulations

how these emotions influence the specific actions taken by individuals.

Some research efforts [34, 121] explored the epidemiological susceptible–infected–susceptible (SIS) model, with a specific focus on its application to represent emotion contagion, particularly in emergency situations. This adaptation of the SIS model provides a framework to examine and simulate the spread of emotions within a crowd during emergency scenarios. Some researchers [34, 66] used an improved emotional contagion model by upgrading the SIS model. Epidemiological models operate similarly to the spread of a contagious disease, exerting a more pronounced effect on agents when the number of infected agents, such as those exhibiting heightened panic behavior, is higher. On the other hand, Bosse's thermodynamics-based model [12] illustrates that models rooted in thermodynamics tend to yield superior results compared to epidemiological models. This superiority can be attributed to the inadequacies of the contagion mechanism inherent in epidemiological models.

Tsai et al. [102] developed a multi-agent evacuation simulation tool called ESCAPES, in which an agent can adopt the emotion of other agents who possess the strongest mood or have a special identity.

Minh et al. [105] developed a model of emotions that considers their dynamics and propagation, integrating it into an evacuation simulation. Their model considers both the dynamics of emotions, including when emotions appear and how their intensity level evolves over time, as well as the propagation of emotions. This includes how emotions are "sent" and "received" and how a received emotion influences the receiver.

Another emotion contagion model called the ASCRIBE model [14], on the other hand, is a multi-agent-based continuous group emotion contagion model that treats emotions as a collective entity. In another study by Cho et al. [24], the authors proposed the integration of the well-established BDI model (Belief–Desire–Intention) to simulate crowds. In this approach, agents are driven by desires (goals), guided by certain beliefs (knowledge of the world), and motivated to take actions (intentions) to fulfill these desires. This framework enables individuals to exhibit realistic behavior by dynamically adapting their actions based on sensed information in a dynamic and evolving environment.

This section discusses using psychological perception theories to deepen insights into agent environment interaction, enhancing behavior modeling. It covers research on appraisal theory, stress modeling, and emotion contagion.

4.4 Environmental factors

Environmental factors typically include evacuation scenarios and geometric constraints. Crowd evacuation stands out as one of the most extensively studied topics in the field of crowd modeling, with numerous works focusing on simulating evacuations during events such as fires [86] and examining how panic levels influence agent behavior [61, 120]. Many of these studies incorporate path planning models and consider other evacuation factors such as interaction between agents [16, 55, 83], addressing complexities in environments [81], investigating the evolution of group emotions [58], the effect of crowd density [90], and enabling virtual agents with the perception of emergency events to simulate crowd evacuation [15].

Ren et al. [86] introduced an agent-based modeling and simulation (ABMS) approach to model crowd evacuations during fire emergencies. The model incorporates an agent with diverse attributes, such as age, velocity, and panic scale, and studies their influence on crowd behavior. Many other studies have explored agent behavior during emergencies by investigating emotion contagion in groups [13, 26, 44, 47, 67, 68, 114]. Notably, the research in [68] emphasizes the impact of personality and emotion contagion, considering both individual and group emotions. It specifically highlights the substantial influence of group emotion on the behavioral patterns of agents in the context of emergency evacuations.

Some research works [82–84] incorporated the notion of way-finding through inter-agent communication and diverse agent roles, such as leaders and followers. These elements enrich an agent's cognitive map of the environment, leading to demonstrably enhanced building evacuation performance and more realistic crowd behavior in unfamiliar environments.

Braun et al. [15] proposed an approach for simulating virtual human crowds in emergency scenarios, integrating elements from previous work and incorporating a physical model based on the "social forces" [43]. They focused on guiding individuals toward a target while avoiding obstacles.

Moreover, geometric constraints in certain situations can trigger panic within a crowd, leading to the abrupt onset of an evacuation scenario. Such constraints encompass factors like an insufficient number of exterior exits, inadequate width of exit doors [80], obstructed passageways, stairs, and doors. For example, a research study [39] investigated and modeled the impact of room door size, main exit size, desired speed, and friction coefficient on evacuation efficiency. This study sheds light on the importance of geometric factors in influencing the effectiveness of evacuation procedures.

This section examines how environment influences crowd behavior, focusing on panic effect, evacuation simulations, and group dynamics. It discusses agent interaction, emotions, and geometric constraints on evacuation, underscoring the importance of simulating realistic emergencies.

4.5 Group dynamics/social distancing

Diverse focuses within crowd behavior modeling emerge as some researchers concentrated on capturing and modeling gap-seeking behavior in crowds [65], while another subset of studies [4, 52, 85, 95] delved into modeling leader-follower group dynamics. For example, Qiu and Hu [85] incorporated Festinger's social comparison theory [32] to model agents' dynamic grouping behavior. The theory highlights that when humans encounter uncertainty, they tend to compare themselves to others who are similar to them and strive to minimize any perceived differences. In emergency situations, where uncertainty is increased, the influence of social comparison on human decision-making becomes more pronounced.

Additionally, numerous research studies have extensively explored the impact of social distancing on crowd behavior and have used agent-based simulations to predict the spread of COVID-19 infection during the pandemic [3], to investigate the effects of disruption of social distancing [29] or to simulate crowd behavior during a pandemic context and study the effect of social distancing on crowd evacuation efficiency [59]. In a previous study by Capobianco et al. [19], intricate interactions among individuals were modeled to predict the prevalence of infected individuals based on partial observations, including test results, the presence of symptoms, and past physical contacts.

Some research studies investigated group dynamics and their impact on evacuation scenarios. For example, Pelechano et al. [83] proposed an evacuation simulation model that integrates various social traits of agents such as followers, untrained and trained leaders. This breadth of research in the domain underscores the multifaceted nature of crowd behavior modeling.

This section covers how crowd behavior modeling incorporates environmental factors and group dynamics, focusing on realistic simulations of emergency evacuations and the effects of social distancing.

4.6 Physiology

Some research studies have incorporated the physiological factor of agents to model its impact on crowd simulations. For example, in the study of [113], the concept of physical strength consumption is integrated to capture its influence on agent movement. Another study [70] models pedestrian behavior by considering various physiological factors such as walking direction, speed, and occurrences of body collisions during overcrowding.

Furthermore, Zheng et al. [118] investigated four essential physiological characteristics -gender, age, health, and body shape. This integration of agent physiology enhances the realism of crowd simulations by taking into account the various factors that influence individual movement patterns in a crowd. Studies incorporate physiological factors into crowd simulations, improving realism by considering diverse influences on individual movement patterns.

4.7 Roles and needs

In a crowd, individual agents often pursue specific goals, such as reaching a destination, navigating obstacles, or following a leader. These goals significantly shape their actions. Additionally, researchers have made increasing efforts to explore crowd modeling with a focus on individuality. In such simulations, virtual agents have behaviors customized to their social roles and personal requirements. For example, Musse and Thalmann [74] outlined a crowd simulation framework that includes sociological factors such as relationships, groups, and emotions. Another research study by Stocker et al. [98] has introduced the notion of priming for virtual agents. In this context, agents are prepared for specific actions based on the presence of other agents and events in their surroundings.

In a study conducted by Shao and Terzopoulos [92], urban environments were illustrated with autonomous pedestrians categorized into various groups, including commuters, tourists, performers, and officers. Each character type is associated with hand-coded action selection mechanisms, contributing to a diverse range of behaviors. On the other hand, some researchers employ parameterized systems to represent agents' goals and behaviors [7, 10]. For example, the CAROSA framework [2] enables the specification and control of actions for realistic human-like characters by incorporating four distinct types of actions: scheduled actions based on predefined roles, reactive actions triggered by contextual events, opportunistic actions driven by explicit goals, and aleatoric or stochastic actions. This approach adds depth and complexity to agent behaviors.

Several research groups have focused on integrating roles into virtual agents. Hayes-Roth and colleagues were pioneers in this area, developing some early virtual roles [41]. Their interactive intelligent agents collaborate to improvise behavioral sequences that adhere to instructions, express unique styles, observe social conventions, and achieve objectives. Later, Li and colleagues proposed an agent-based simulation framework [60], in order to create virtual populations enriched with various social-psychological factors, including the integration of social roles. They simulate virtual populations with predefined social roles, delineating the purpose of each virtual human's existence. These agents can execute actions such as scheduled, reactive, and need-based behaviors. Furthermore, the introduction of role switching based on schedules, reactions, and needs allows realistic behavioral variations throughout the day. This comprehensive approach facilitates a nuanced representation of crowd behavior, capturing the myriad motivations and interactions of individuals within the simulated environment.

This section explored studies that emphasize individuality in virtual agents, showcasing behaviors tailored to their unique goals and roles, with varied action selection for enhanced realism in simulations.

5 Discussion and open questions

Although researchers have studied crowd simulation extensively, there are still some major challenges to tackle. These challenges arise from the complicated and ever-changing behaviors we see in real crowds that stem from the intricate interplay of complexity, diversity, and dynamic nature inherent in real-world crowd behaviors.

Drawing insights from this literature review, the following open questions emerge as imperative focal points for future research for agent-based crowd simulations:

- A comprehensive crowd simulation, striving for realism, should incorporate various psychological and environmental factors such as interpersonal relationships and social dynamics. Collaboration with experts in human behavior and psychology or empirical studies observing human behavior in various contexts can help in refining these models to better reflect real-world scenarios.
- Further research that integrates a variety of behavioral factors, including personality traits, perceived emotions, and group dynamics into machine learning models for crowd simulation holds substantial promise to advance the field. Collecting high-quality, diverse datasets from real-world observations and incorporation of these behavioral aspects are instrumental in enhancing the performance of machine learning models.
- Despite significant advancements in crowd simulation, the field lacks standardized, widely accepted evaluation methods to validate the realism of simulated crowds. A working group of researchers and industry experts could work on developing a set of standardized test scenarios, metrics, and validation protocols to assess the realism and accuracy of crowd simulations.

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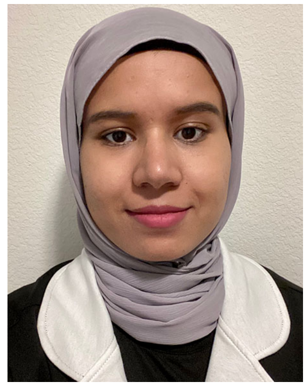

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