Machine Intelligence Research
www.mi-research.net
21(3), June 2024, 452-480
DOI: 10.1007/s11633-022-1405-5

Collective Movement Simulation: Methods and Applications

Hua Wang[1,2,3] Xing-Yu Guo[1] Hao Tao[4] Ming-Liang Xu[1,2,3]

[1] School of Computer and Artificial Intelligence, Zhengzhou University, Zhengzhou 450001, China
[2] Engineering Research Center of Intelligent Swarm Systems, Ministry of Education, Zhengzhou 450001, China
[3] National Supercomputing Center in Zhengzhou, Zhengzhou 450001, China
[4] China Ship Development and Design Center, Wuhan 430060, China

Abstract: Collective movement simulations are challenging and important in many areas, including life science, mathematics, physics, information science and public safety. In this survey, we provide a comprehensive review of the state-of-the-art techniques for collective movement simulations. We start with a discussion on certain concepts to help beginners understand it more systematically. Then, we analyze the intelligence among different collective objects and the emphasis in different fields. Next, we classify existing collective movement simulation methods into four categories according to their effects, namely versatility, accuracy, dynamic adaptability, and assessment feedback capability. Furthermore, we introduce five applications of layout optimization, emergency control, dispatching, unmanned systems, and other derivative applications. Finally, we summarize possible future research directions.

Keywords: Collective movement simulation, multiple objects, multiple discipline, simulation effect, collective intelligence.

Citation: H. Wang, X. Y. Guo, H. Tao, M. L. Xu. Collective movement simulation: Methods and applications. *Machine Intelligence Research*, vol.21, no.3, pp.452–480, 2024. http://doi.org/10.1007/s11633-022-1405-5

1 Introduction

Creatures' movement behavior shows superior wisdom, which is the inexhaustible power and rich source of human creativity[1]. Collective movement simulations describe how an object changes its location according to the state of its neighbors and environment system[2–8] on the basis of knowledge from mathematics, physics, psychology and computational science[9]. They focus on reproducing collective movement behavior and promoting the migration/iteration of collective intelligence, which is of great significance for decision-making, control, planning, etc.

For beginners, it is difficult to realize a high-quality collective movement simulation. The main reasons are as follows. Firstly, there are various types of collective objects, including living intelligent objects (such as birds[10, 11], fish schools[12], bees[13], ant colonies[14], humans, etc.), non-living intelligent objects (such as robots, unmanned aerial vehicles, etc.)[15–17], and the combination of the above (e.g., vehicles, manned aircraft, etc.)[18]. Secondly, there are many factors affecting collective movement, not only including diverse collective behaviors (such as foraging, migration, obstacle avoidance, escape, cooperation, confrontation, and conformity, etc.), but also including inter-individual differences (such as personality, emotion, experience, etc.). Characterizing the above behaviors and reproducing collective intelligence attract lots of researchers from different fields. There have been lots of reviews to summarize the above work so far[19–25]. They summarize the difference between homogeneous and heterogeneous collective simulation methods. There are still some problems: Firstly, lots of collective movement simulation methods from different fields are confusing for beginners, which increases their learning difficulties. Secondly, there is little analysis of the intelligence among different kinds of collective objects, which may lead to the lack of horizontal intelligence exploration. Last but not the least, the classifications of existing methods are usually based on the properties of the methods themselves, such as macro/micro methods and data-driven/model-driven methods, etc. However, users often prefer to find one type of method that can meet their application requirements quickly, and then narrow the scope to choose the best method, which is impossible according to existing classifications.

In order to address the above problems, this paper organizes the related work on collective movement simulations. This paper first introduces related concepts, and then analyzes the related work from different collective

Review
Manuscript received on July 15, 2022; accepted on December 13, 2022; published online on January 12, 2024
Recommended by Associate Editor Jingyi Yu
Colored figures are available in the online version at https://link.springer.com/journal/11633

objects, fields, and effects. Finally, applications and discussions are presented. The main contributions of this paper are as follows:

1) Show related concepts about collective movement simulations to help beginners clear the context.

2) Discuss intelligence among different collective objects according to the latest research.

3) Summarize the focus of different fields on collective movement simulations.

4) Classify existing collective movement simulation methods according to their application effect, which can help users quickly find the methods that they need.

The outline of this paper is as follows. Section 2 introduces concepts about objects such as flock, swarm, crowd, group and self-driven particles, clarifying the concept of collective movement, and distinguishing the relationship among model, simulation and animation. Section 3 firstly analyzes the intelligence of four types of objects, including creatures, crowds, robots and vehicles, and then shows a lateral analysis. Secondly, it summarizes the focus of research on collective movement simulations in four fields: life science, mathematics/physics, information science and public safety. Then, existing methods are divided into four categories according to their application effects: versatility, accuracy, dynamic adaptability and assessment feedback capability, and the related methods involved in each category are introduced in detail. Section 4 shows the application of collective movement simulations in layout optimization, emergency control, dispatching, unmanned systems, and others. Section 5 summarizes and looks forward to this paper.

2 Concepts

This section introduces some concepts about collective movement simulations to help beginners understand collective movement simulations more systematically.

2.1 Objects of study

The research objects of collective movement simulations are a set of objects that interact with each other. Researchers introduced flock, swarm, crowd, group, self-driven particle and so on to describe the above object set. Here we summarize the differences among these concepts.

Flock. The first model of flocking behavior is proposed by Reynolds[11], mainly referring to flock of birds. Considering that flocking behavior also exists in other living objects, such as a herd of land animals, or a school of fish, etc., Kownacki et al.[26, 27] proposed a broader definition of flock: a group of objects that exhibit this general class of polarized, noncolliding, aggregate motion. Kownacki et al.[26, 27] subsequently introduced the well-known flocking algorithm, which is widely applied to multi-agent control. Then lots of scholars have continued the above broader definition. For example, Vicsek and Zafeiris[2] introduced that flocking motion occurs in the system, in which the units (living and nonliving) are quite similar. Olfati-Saber[28] indicated that flock refers to a large number of interacting agents with a common group objective.

Swarm. The term of swarm comes from the idea of flock. The swarm mainly refers to swarm intelligence coming from the swarming behavior of social insects[29]. Millonas[29] introduced that the swarm is a collection of simple locally interacting organisms with global adaptive behavior. The application of the famous particle swarm intelligence optimization method is used for artificial life[30]. Subsequently, scholars have used some bionic knowledge for the optimization of swarm intelligence methods[31–33].

Crowds. Some researchers consider that crowds are equivalent to human crowds[34–36]. Some other researchers consider that a crowd is human and human-like groups. For example, Xu et al.[24] introduced that crowds refer to complex systems containing collections of individuals, such as human groups and vehicle flows. Gibelli and Bellomo[9] introduced that a crowd is composed of sufficient interacting individuals, and there is a collective intelligence, or a self-organizing phenomenon.

Groups. Members within a group usually have social relationships and intend to move together[37, 38]. The scale of a group is no restriction: two vehicles, three persons and a thousand animals, etc. The internal relationship of one group is also no restriction: following a leader, turning around, etc. However, there is only one internal relationship in one group. Ren et al.[39] believed that groups in a crowd have different properties.

Self-driven particles. Self-driven particles, firstly proposed by Vicsek, refer to particles that appear self-ordered motion through biologically motivated interactions[40]. It is used to describe the phase transition from disordered to large-scale ordered movement. Helbing[41] described self-driven particles as a simplified representations of the dynamic behaviors of cells, animals, and humans[42].

In conclusion, sometimes one concept owns different meanings according to different needs. However, there are still subtle differences among them. For example, the interactions among objects in a flock or a swarm are always simple. There is usually only one type of interaction within a group. The interactions among objects in a crowd are personalized and complex. For the collective scale, there is no strict restriction on the size of a group or a self-driven particle system, in which both large and small are all workable. Collective movement behavior may disappear if the size of a flock/swarm/crowd is too small. Table 1 shows some detailed comparisons.

2.2 Content of study

Collective movement is a type of collective behavior. There are many types of collective behavior in the field of

Table 1 Comparisons among flock, swarm, crowd, group, self-driven particles

Concept	Object of study	Internal interactions	Scale	Application
Flock	Initially refer to birds	Simple	Large	Intelligence optimization
Swarm	Initially refer to insects	Simple	Large	Intelligence optimization
Crowd	Mainly refer to human	Personalized and complex	Large	Control and optimization
Group	Without any restrictions	One	More than one	–
Self-driven particles	Particles that have self-ordered motion	Unconstrained	More than one	–

bionics, such as aggregate behavior[11], schooling behavior of fish[12], division of labor behavior[13], foraging behavior of ant colonies[14], panic behavior[43] and conformity behavior[44] of crowds, migration behavior of animals[45], flickering behavior of firefly swarms[46] and hunting behavior of whale schools[47]. As a behavior, the collective movement behavior is influenced by other behaviors. For example, the different division of labor in bees leads to different movement purposes[13], the concentration of pheromones affects the movement path of ants[14], panic affects the movement speed and direction of crowds[43], and the brightness of firefly flickering affects the movement direction of individuals in its vicinity[46].

Collective movement is, of course, also a type of movement. For individuals within the collective system, their movement behavior can be further divided into numbers of sub-movement behaviors. For example, Reynolds considered that collective movement behaviors include seek, flee, pursuit, evasion, offset pursuit, arrival, obstacle avoidance, wander, path following, wall following, containment, flow field following, unaligned collision avoidance, separation, cohesion, alignment, flocking, and leader following[48]. Helbing et al.[49] considered that collective movement behaviors in a crowd stamping include acceleration, mutual obstruction, shoving, and falling. Obviously, sub-movement is also influenced by other movements.

There are also some subtle differences among collective movement simulations, collective movement modeling and collective movement animation. Modeling refers to the creation of a model that approximates an event[50]. Simulation is a time-varying representation of the event, which can be described by a mathematical model or a symbolic model[51, 52]. Animation is a term that comes from the virtual reality and graphics. Simulation can drive animation and it is often used as the engine for creating actions in computer animations[50].

3 Classification

This section introduces three classifications for existing collective movement simulation methods according to their research objects, fields and effects.

3.1 Objects

According to the intelligence of collective movement, the research objects are divided into four categories: creatures, humans, robots and vehicles. The relationships among them are shown in Fig. 1. Creatures contain a wealth of intelligence. Humans have evolved intelligence over a long evolutionary process to be smarter than creatures. The intelligence of the robots is transferred from the creature and human intelligence. And the movement of vehicles is jointly determined by the human-vehicle, reflecting the fusion of human and robot intelligence.

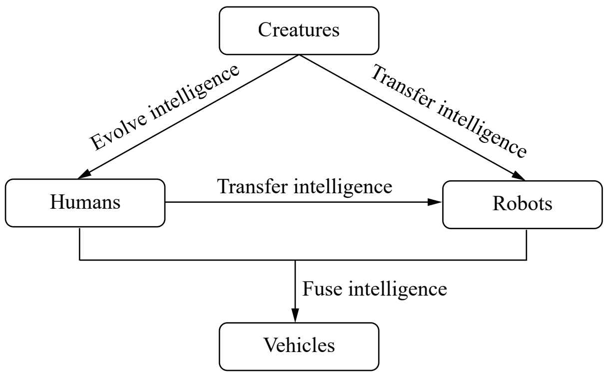

Fig. 1 Intelligence relationship among different objects

3.1.1 Creatures

The collective movement from creatures contains rich intelligence.

In a flock of birds, individuals interact with others to obtain useful information[53]. They also scan the environment around them and detect danger to increase the survival advantage of the whole flock[54, 55]. As the scale of the flock increases, individual vigilance decreases, but the risk of being attacked does not increase[56]. Similar to the flock of birds, in a school of fishes, individuals obtain a larger perceptual range through local visual interactions to reduce risks[57, 58].

In a swarm of ants, individuals release and perceive pheromones along their paths when searching for food. The concentration of pheromone characterizes the distance to the food source, with higher a pheromone concentration indicating a shorter distance to the corresponding path. Then they can search the shortest path under the direction of pheromones[59−61].

In a group of wolves, individuals perceive the environment around them to detect danger. In addition, there are social hierarchies within the pack. The division of labor is clear, which is constantly changing with the survival of the fittest to ensure that the leader is always the strongest individual[62].

There are lots of other creatures that contain intelligence[63–66]. Here we don't list them all. These types of intelligence have provided a lot of inspiration for bionomics scientists and have been widely applied to multi-objective optimization problems[67–71].

3.1.2 Humans

The collective movement intelligence from human crowds may be inferior to creatures in some respects. However, as the highest intelligence possessor on earth, their significant physiology, personality, culture, emotion, social, political, and cognition lead to autonomy, flexibility, and diversity of crowd movement[72, 73]. Next, we take emotion and political abilities as examples.

Emotion is a short-term psychological state of human beings, which has a great influence on the movement of the human crowd[74–76]. For example, human panic is easier to be generated and spread in emergencies[77], which manifests themselves in moving faster movement, following others, pushing and shoving between individuals, blocking at bottlenecks/exits, and triggering crowd stampede[78]. However, after the guidance of security personnel, individuals can gradually change from negative emotions (panic, anxiety, fear, impatience, anger) to positive emotions such as calmness and optimism[79], such as security guards guiding humans to the exit and teachers guiding students to evacuate from the school building[80]. In crowd queuing events (automated teller machines (ATMs), subway stations, bus stops, service windows, etc.), individual queuing time and urgency can affect their patience and friendliness, resulting in negative emotions that confuse the queuing order. When many individuals in the crowd have negative emotions, it may cause queue confusion[81].

Different political views lead to different values. Crowds gathering is a typical political rally, such as a presidential election or a parade. Individual movement is influenced by its neighborhoods, and groups with different political views may erupt into violent conflict[82]. In crowd violence incidents, antagonism plays an important role, which refers to the hostility of individuals with different identities, such as police and thugs[83].

In conclusion, movements of human crowds are more complex than creatures, with more influencing factors and more powerful individual intelligence.

3.1.3 Robots

The collective movement intelligence of robots (robots, unmanned vehicles, drones, etc.) is machine intelligence, which usually comes from bionic intelligence. Here we show how to model individuals in robot collections to generate collective intelligence according to the following two types.

The first type is transformed by a kind of bionic intelligence. Doctor et al.[84] regarded each mobile robot as a particle, and use the particle swarm algorithm to guide collective robotics to search for single and multi-target. Liang and Lee[85] considered each robot as a bee, and use an efficient artificial bee colony algorithm to adjust its role according to the search results so that the multi-mobile robots can reach the specified target without collision. Wang et al.[86] regarded each uninhabited combat air vehicle as a bat, and perceive the distance by echolocation to ensure that individuals follow the shortest path each time. Qu et al.[87] treated the drones as gray wolves, where three individuals with better adaptation form the leading wolf swarm and influence the rest, which generate high-quality paths for the unmanned aerial vehicles (UAVs) in a 3D complex flight environment. Pandey et al.[88] considered the UAVs as a firefly swarm, where individuals exchange local information in their variable neighborhood and choose to go closer to others that are better than themselves, which generates feasible trajectories from source to destination for the UAV.

The second type is to blend various kinds of bionic intelligence for better performance. Das et al.[89] considered each robot as a particle and combined an improved gravitational search algorithm and improved particle swarm optimization to update the acceleration and velocity respectively, which minimizes the multi-robot motion time and path length in a clutter environment. Qu et al.[90] treated UAVs as a wolf pack. They use the grey wolf optimization algorithm to search for possible solutions and then optimize the solutions using the modified symbiotic organisms search algorithm, which can generate effective and safe paths for UAVs in complex and dangerous environments. He et al.[91] regarded UAVs as a particle swarm. They update each particle's position using improved particle swarm optimization, and then adopt a modified symbiotic organisms search algorithm to boost the local search capability of the particle, which can yield feasible paths for UAVs in 3D complex terrain environments.

Theoretically speaking, we can use many types of bionic intelligence to control the collective movement of robots. Therefore, in some way, robots can be more intelligent than creatures. However, lots of human behaviors have not been artificially generated, and robots are less intelligent than human beings.

3.1.4 Vehicles

The vehicles can essentially be seen as a fusion of human and robot intelligence, which contains both driver perception decisions[92] and intelligent control that comes with the vehicle design. Therefore, the vehicles movement shows complex traffic phenomenon[93].

A driver uses visual, auditory, vestibular and somatosensory sensory systems to perceive the environment. Then he controls the longitudinal and lateral movement of a vehicle by manipulating the throttle, brake, and steering wheel. And the vehicle is able to cope with complex dynamic traffic situations with the driver's high intelligence. Among them, the visual perception plays a crucial role. The central vision perceives the geometry of roads and peripheral vision perceives the speed and relative position of surrounding vehicles. The closer vision helps the driver to control the vehicle laterally and the farer vision helps the driver to achieve smoother maneuvers[94].

Similar to humans, there are many factors that affect drivers' driving behavior, such as weather conditions, answering/making calls, entering text messages, eating, driving habits, proficiency in driving skills, age, and gender[95, 96]. Studies have indicated that up to 20%–30% of traffic accidents are caused by physiological reasons such as driver fatigue and distraction. Music with different emotional values has different effects on driving behavior. Cheerful music greatly distracts the driver and reduces lateral control. Drivers listening to sad music cause them to slow down and stay in the current lane[97]. Driver emotion is also an important factor, relaxed and positive emotions can help drivers make rational judgments[98], angry emotions would decrease drivers' risk perceptions, and fear can improve drivers' alertness[99].

In all, drivers determine the performance of the vehicle's underlying motor control, while vehicle dynamics and kinematic constraints affect drivers' operating behavior. In other words, the driver's decisional intelligence and the vehicle's control intelligence jointly determine the traffic behavior.

3.2 Fields

There are rich and wonderful connotations of collective movement. Researchers in a variety of fields, including life science, mathematics, physics, information science and public safety, have conducted extensive research on this topic.

The relationship among these fields is shown in Fig. 2. Life science and mathematics/physics are basic science, with the former focusing on revealing the nature of the collective movement and the latter on describing it by constructing theoretical models. Information science and public safety are applied science, with the former mainly extending existing mathematical models or employing other techniques to portray collective movement, and the latter integrating the application of the above existing methods to serve the real world. Next, we will give some detailed descriptions.

Life science. To some extent, life science is a basic science discipline of quantitative analysis, which generally uses observation and description, statistical experiments, comparative analysis, etc., to discover the biological roots of collective movement behavior generation[100]. Li et al.[101], by studying the unique interactions of neuronal activity during competitive foraging in mice, found that competition among animals within a group is not only related to individual health, but also strongly in-

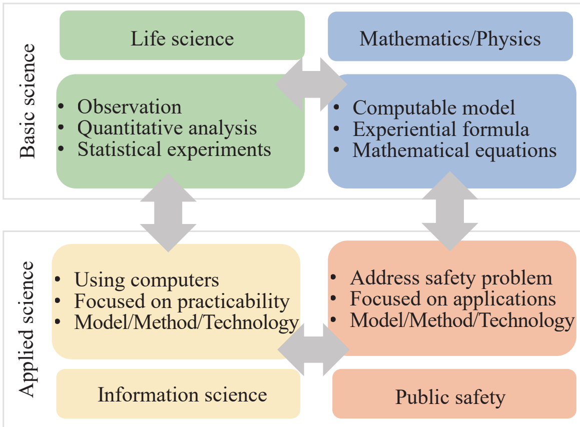

Fig. 2 Relationship among life science, mathematics/physics, information science and public safety.

fluenced by neural signals Padilla-Coreano et al.[102] experimentally revealed how the mammalian brain encodes social hierarchies and uses hierarchical information to shape its own social competitive behavior. Lyu et al.[103] investigated the discovery of regions within the drosophila brain involved in goal-directed navigation, which can update spatial perception according to different movement angles and body angles in order to compute coordinate transformations and movement directions. Bon[104] by observing the mass phenomenon caused by the French Revolution, argued that these masses were often susceptible to emotional agitation losing rational judgment, which led to the collective mind. Scholars in this discipline focus on the discovery of correlations, laws and rules, and do not construct computable models of these findings.

Mathematics and physics. Similar to the life science, mathematics and physics are also basic science disciplines. The difference is that mathematics and physics require not only discovering the origin of collective movement behavior, but also constructing computable mathematical models for it through analytical and numerical means. Helbing and Molnár[105] proposed a classical social force model to simulate crowd evacuation behavior based on Newton's second law. This model has been used to successfully simulate the "fast is slow", exit selection, and panic behaviors of crowds during evacuation[43]. Hughes[106, 107] combined continuity equations, fundamental diagrams, and potential fields based on continuum medium theory, assuming that each agent has the same mass and velocity probability density function, for high-density crowd simulation. Silverman et al.[108, 109] constructed a predictive theory of pedestrian flows based on conservation laws, symmetry principles and the spectral properties of the velocity waves. This model allows to describe how a group responds to perturbations to constrain continuum models in polarized populations. The outstanding advantage of mathematics and physics disciplines is that the results are directly available for computer simulations.

Information science. The information science provides a new research paradigm for the study of collective movement simulations for the fields of life science, mathematics and physics. It is the biggest booster of the traditional study policy of "Learning through investigation" to the new research strategy of "Learning through simulation". The development of collective movement simulation technology in this field can be generally grouped into two aspects. One is to progress with advances in life science, mathematical and physics disciplines. When the collective movement simulation technology in mathematics and physics is not fully mature, academics in information fields are more likely to realize the simulation of collective behavior based on some simple rules[11, 12]. With the successive proposals of social force model and fluid models, researchers have been inspired to simulate more realistic and reasonable collective movements with ample details[110, 111]. Chao et al.[112] simulated a mixed traffic scenario of pedestrians, bicycles and cars based on the concept of force, and portrayed in great detail the following and lane changing behaviors of vehicles, collision avoidance and overtaking behaviors of bicycles. The other is directly based on the laws found in life science disciplines, using machine learning and other techniques to build models that describe the mechanisms of collective movement behavior. Examples include, genetic algorithms[113] that simulate genetics, mutation, natural selection, and hybridization in biological evolution, particle swarm optimization algorithm[10], ant colony optimization algorithm[14], artificial bee colony optimization algorithm[13], firefly algorithm[46], whale optimization algorithm[47], and rat colony optimization algorithm[114].

Public safety. The public safety is a typical applied science. It mainly integrates and applies the above-mentioned results to provide a theoretical basis for the safety level and planning design of buildings, highways, etc. Shen[115] proposed an evacuation simulation model to predict the crowd evacuation performance of buildings, which is adopted for safety evaluation and helps to optimize the internal structure of buildings. Tian[116] reproduced the crowd evacuation process in public areas based on a fluid dynamics model and analyzed the evacuation efficiency of different layouts, which is helpful to improve the building design and shorten the evacuation time of humans. Wagner and Agrawal[117] pointed out that the evacuation time of a crowd does not decrease as the desired speed of the crowd increases, but there is a process of reducing and then growing. If everyone evacuates at the exit at the desired speed, a huge crowding pressure is generated and causes a stampede[118, 119]. Ma et al.[120] combined a pedestrian space analysis model and an agent-based pedestrian model on a geographic information system platform to simulate pedestrians movement for assessing the safety and comfort of complex buildings, which is also applicable to the construction of transportation facilities. Castañeda et al.[121] proposed an intersection traffic simulation method based on the building information modeling approach to analyze and evaluate roadway performance, which is useful to improve the quality of intersection construction. Researchers in this field focus on applying simulation methods to guide real-world planning and construction.

3.3 Effects

In terms of simulation effects, collective movement simulation methods can be classified into four categories: versatility, accuracy, dynamic adaptability, and assessment feedback capability. The following provides a detailed description of the comparisons among them.

3.3.1 Versatility

Versatility refers to the ability of a method to migrate to different scales, scenarios and kinds of objects. According to the level of individual details, it is mainly divided into microscopic models and macroscopic models[122].

Microscopic models

Microscopic models drive collective movement with high level of individual details, and several microscopic models have been developed, primarily including rule-based models, cellular automata models, and social force model.

Rule-based models. Rule-based models usually characterize collective movement through a series of behavioral rules. They have been applied to animals, crowd, and traffic simulations. Reynolds[11] proposed a distributed boids model using three rules of collision avoidance, velocity matching and flock centering to simulate the separation, alignment, clustering, exploration, pursuit and avoidance behaviors of bird flocks. Tu and Terzopoulos[12] suggested a fish intention generation rule to simulate the behavior of artificial fish based on its perception information, habits, and psychological states, etc. Yuan et al.[123] designed rules to simulate interactions between walking companions. Chao et al.[124] successfully reproduced pedestrian-vehicle interactions in mixed traffic.

Rule-based models are simple and easy to implement. However, they are difficult to describe complex behaviors comprehensively, and deadlock caused by rule-to-rule conflicts are unavoidable as the number of rules increases.

Cellular automata models. A cellular automata (CA) model is a discrete computable model that discretizes the space into finite cells. Cells follow specific movement rules, interact with neighboring cells, and evolve according to time steps[125]. The earliest use of CA models to study vehicle and crowd movements was by Nagel and Blue, respectively. Nagel and Schreckenberg[126] applied CA to single-lane micro-traffic simulation[127], and later expanded it to two-lane scenarios[128]. Next, Blue and Adler[129] developed a CA model to investigate unidirectional pedestrian flow, and then proposed a new rule set to extend the CA model to bidirectional pedestrian walkways simulation[130].

A pioneering work is the introduction of the floor field in CA by Burstedde et al.[131], namely the floor field CA model (FFCA). Fig. 3 shows the individual possible transitions and associated matrix of preference M in this model. It is able to translate spatial long-ranged interactions into non-local interactions in time and to reproduce collective phenomena of human crowds. On this basis, the scholars have carried out extensive research. Zhao et al.[132] proposed a continuous FFCA model for the low accuracy of discrete FFCA. Lu et al.[133] added leader-follower rules to extend the FFCA in order to better simulate the movement characteristics of groups (such as friends and families). Kirchner and Schadschneider[134] adopted static floor field to specify regions of space which are more attractive, e.g. an emergency exit or shop windows, and a dynamic floor field describes the pedestrian virtual trace that diffuses and decays over time. This method can simulate complex cases of crowd evacuation.

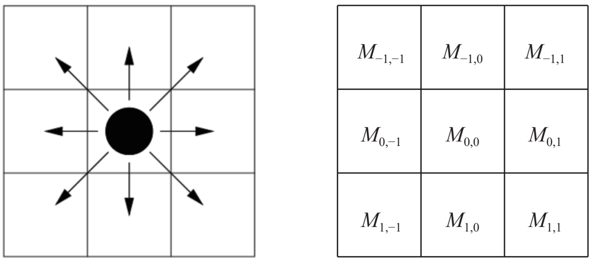

Fig. 3 Individual possible transitions and associated matrix of preference[131]

A well-known variant of the CA model is the lattice gas model[135], which treats pedestrians as biased random walkers for simulating the counterflow of pedestrians in a subway passage. Subsequently, Muramatsu and Nagatani[136] extended this method to the congestion problem of two-way and four-way pedestrian flows, and study the congestion structure in different situations.

To improve the simulation precision of the CA, researchers have conducted a lot of research. Ruan et al.[137] redefined lattice, cells′ states, neighborhoods and transition rules as well as present multi-axle single-cell CA, which generates microscopic vehicle sequences with detailed axle positions. Liu and Shi[138] modeled multi-lane vehicle lane change movement by introducing back-propagation neural networks. Wang et al.[139] imported vehicle following and lane changing rules for different traffic scenarios into the multi-agent CA model. Kirchner et al.[140] introduced a factor affecting pedestrian movement speed, to portray the mutual obstructive effect between pedestrian. Weng et al.[141] proposed a CA model without a step back for pedestrian dynamics, which is able to judge in some complex situations. Yamamoto et al.[142] presented a real-coded CA model, which successfully simulates the oblique motion of pedestrians on grids. Fu et al.[143] introduced individual differences to study the influence of individual personality and psychology on evacuation behavior, and realistically simulate the evacuation behavior of crowds in crisis situations.

Due to the discreteness of the CA models in space, time and state, the calculation speed is fast and the efficiency is high when there are a large number of individuals. However, these models cannot describe interactions among individuals in detail. It is suitable for low-density and simple interaction scenarios.

Social force models. The famous social force model (SFM) was proposed by Helbing and Molnár[105], and individual behavior is determined by (1):

$$m_i \frac{\mathrm{d}\vec{v_i}}{\mathrm{d}t} = m_i \frac{v_i^0\,(\mathrm{t})\,\vec{e_i^0}\,(t) - \vec{v_i}\,(t)}{\tau_i} + \sum_{j \neq i} \vec{f}_{ij} + \sum_{W} \vec{f}_{iW} \quad (1)$$

where the left side is the product of individual mass and acceleration, and the right side is the resultant force on the individual, the first item of the right side is the self-driving force, $v_i^0\,(t)$ represents the desired speed, $\vec{e_i^0}\,(t)$ represents the direction of the desired speed, $\vec{v_i}\,(t)$ represents the current speed, $\vec{f}_{ij}$ represents the repulsive force between pedestrians, and $\vec{f}_{iW}$ represents the repulsive force between the pedestrian and the obstacle.

The SFM has received widespread attention since it was proposed, leading to lots of derivative works. Lakoba et al.[144] modified the original SFM for repulsive forces, social force direction and pedestrian perception of the direction in which the target is located to generate a more realistic simulation. Based on this, new expressions for repulsive forces[145−147] are proposed. Pascucci et al.[148] put forward a multilayer SFM, to simulate different traffic conditions from free flow to congestion. Huang et al.[149] linked three sources of social forces to research vehicles interactions. Jiang et al.[150] introduced dynamic navigation field, which can reproduce various scenarios of pedestrian evacuation, like self-organized arching and queuing phenomena, and is also able to capture pedestrian behavior, like exit selection and path choice.

In the real world, each individual is diverse and heterogeneous, and there are great differences in their innate character. Therefore, social and psychological factors are also incorporated into SFM. Pelechano et al.[151] proposed a layered behavioral architecture for the simulation of movement with high-density autonomous crowds, which combines the psychological and geometric rules with a SFM. Wu et al.[152] quantified the physical and psychological attributes of pedestrians by introducing individual physical and psychological coefficients respectively, to construct a pedestrian heterogeneity-based SFM.

The SFM describes the interactions among individuals and between individuals and the environment, effectively reproducing the self-organization of collective movements.

Rule-based models, CA models and social force models focus on descriptions of individual behavior in detail. Among them, rule-based models are easiest, but CA models and social force models do not introduce the deadlock problem. Compared with CA models which solve individual behaviors in discrete space, social force models can show more complex and diverse individual behaviors.

Macroscopic models

Macroscopic models describe collective movement in low-level individual details, represented by velocity, density, flow, etc., mainly including continuous models and potential field models.

Continuum models. Many properties of a collective at high densities are similar to a fluid, hence the term "thinking fluid". Fluid dynamics and gas dynamics have inspired scholars to migrate and apply them to vehicle and crowd simulation as early as the 1970s. McDowell[153] applied the idea of fluid dynamics and propose partial differential equations describing multi-lane traffic flow. Henderson[34] posed a hydrodynamic model describing pedestrians movement, which assumes that each pedestrian has the same mass and velocity probability density function. Subsequently, Helbing[154] came up with a hydrodynamic method based on the Boltzmann-like gas-kinetic model, by taking the direction of pedestrian motion and the anisotropy of interactions between pedestrians into account.

A landmark model in traffic flow simulation is the LWR model[155], allowing for larger flows when the traffic density is moderate. The model adopts the first-order mass conservation equation in fluid mechanics to derive the continuity equation describing the motion of traffic on a long straight road, as shown in (2):

$$\partial_t \rho + \partial_x (\rho v) = 0 \tag{2}$$

where ρ is the density, v is the velocity at the corresponding position, and v does not increase as ρ increases. ρ is from 0 to the maximum density ρ_m, which is determined by the traffic congestion situation.

Continuum models are able to simulate large-volume, high-density collective movement, which has stimulated the research interest of scholars. Chenney[156] suggested the flow tiles model based on the design of velocity fields in small constrained regions called tiles. Coscia and Canavesio[157] modeled pedestrian motion strategies and panic behavior using mass conservation equations and boundary conditions based on the continuous medium theory. Narain et al.[158] posed a hybrid continuous medium approach that scales to simulate dense crowds of up to 100 000 individuals. Bellomo et al.[159] parameterized the mean velocity for constructing mass conservation equations and fluid dynamics equations to model homogeneous behavioral crowd movements, heterogeneous walking strategy, and social behaviors. Mohan and Ramadurai[160] developed an existing second-order continuum traffic flow model in order to model heterogeneous traffic flows, using area occupancy rather than density to describe traffic flow concentrations. Liang et al.[161] put forward a second-order pedestrian model including two types of equations: a continuity equation and a set of transmission equations.

Continuous models focus on the study of large-scale collective movement trends according to the laws of physics. They are suitable for high-density scenarios. However, the simulation results lack diversity, which means that each agent has uniform speed and single behavior.

Potential field models. Potential field models are another model to describe collective movement from a macroscopic perspective, and the most common method is the artificial potential field (APF) method[162], which calculates repulsive forces away from obstacles and attractive forces close to the target.

The attractive potential field is shown in (3):

$$U_{att} = \frac{1}{2} k_{att} (x - x_d)^2 \tag{3}$$

where k_{att} is the position gain of the attractive potential field, x is the current individual position, and x_d is the goal position.

The repulsive potential field is shown in (4):

$$U_{rep} = \begin{cases} \frac{1}{2} k_{rep} \left[\frac{1}{x_g} - \frac{1}{\rho} \right]^2, & \text{if } x_g \leq \rho \\ 0, & \text{if } x_g > \rho \end{cases} \tag{4}$$

where k_{rep} is the gain factor of the repulsive potential field, x_g is the distance between the individual and the obstacle, and ρ is the influence distance of the obstacle.

From the above equations, an agent is affected by the superposition of an attractive potential field and multiple repulsive potential fields.

However, the conventional APF method has two drawbacks, namely, target unreachability and local minima. Therefore, researchers have proposed improvement from two aspects.

One is to optimize internal parameters. Chen and Li[163] modified the APF function to increase the attractive field and decrease the repulsive field when approaching an obstacle. Lin and Hsieh[164] proposed the concept of a rotating repulsive field by introducing a target factor in the repulsive field to provide feasible directions. Song et al.[165] presented a predictive APF with three modifications, namely angle limitation, velocity adjustment, and potential prediction, as a way to improve the feasibility and flatness of the generated paths. Chen et al.[166] avoided the local minima problem by setting virtual obstacles and targets, and used a simulated annealing algorithm to search for the optimal parameters of the artificial potential field.

The other is to combine it with other methods. Zheng et al.[167] developed a multi-agent path planning algorithm based on hierarchical RL and APF. Noguchi and Maki[168] advanced an APF based on binary Bayesian filtering with RL to create paths in a simulated environment. Li et al.[169] defined the concepts of distance reinforcement factor (DRF) and force reinforcement factor (FRF), and decomposed the reward function into two parts by the DRF and FRF.

Potential field models abstract the environment into a virtual force field, with a simple formula and fast calculation. However, it is not suitable for the environment with more complex obstacles.

In the above two types of models, each agent does not consider the individual level interactions between others and the environment. The difference is that the continuous models represent collective movement as a continuum flow, while the potential field models calculate the resultant force for each agent.

3.3.2 Accuracy

Accuracy refers to the simulation results close to the real situations. According to the level of the data, it is mainly divided into microscopic data-driven methods and macroscopic data-driven methods.

Microscopic methods

Microscopic data-driven methods use microscopic data (trajectory) to simulate collective movement[170].

This approach represents collective movement in terms of "state-response" value pairs. A series of "tate-response" value pairs (representing how the collective would react in different states) are extracted from real videos. In the simulation, the current "state" of the individual is calculated, and then the current "state" is matched with the "state" in the extracted data. Finally, the "response" corresponding to the best matching "state" is used to drive the collective movement. Lerner et al.[171] processed the real crowd data into a large number of instances and stored them in the database. In the simulation stage, the crowd movement is driven by finding the instance most similar to the current simulated scene in the database. Lee et al.[172] proposed an action selection mechanism based on regression. Later, Lerner et al.[173] further improved this method by annotating the trajectories of agents with actions-tags to enhance the interaction between the agent and the environment.

In recent years, with the continuous improvement of neural network methods, micro data-driven methods have been further developed. Instead of searching the database to find the optimal action, the neural network is trained directly with "state-response" pairs. Wang et al.[174] established a car-following model based on gated recurrent unit NN, which takes the observed speed, speed difference and position difference in the past several time intervals as inputs. Bi et al.[175] combined a convolutional NN and a recurrent NN to simulate the movement of vehicles and pedestrians at intersections. Wei et al.[176] used a back propagation neural network (BPNN) with two hidden layers to simulate real crowd behavior, with less simulation error. Yao et al.[177] suggested that human crowd movement characteristics contain both physical and psychological directions. They extracted the physical attributes of crowd motion (position, velocity) from real data, and used them to quantify the social attributes of the crowd (cohesion, collectivity). Zhao et al.[178] designed an ANN containing two sub-model to simulate the magnitude and direction of pedestrian velocity using semicircular forward space based sub-model and a rectangular forward space based sub-model, respectively. Xie et al.[179] simulated the vehicle lane change decision using a deep belief network (DBN) and long short-term memory (LSTM), which produces simulated trajectories that are almost identical to the real trajectories. Bi et al.[180] coupled a random forest model with a BPNN to simulate the vehicle lane change decision process and vehicle lane change speed, respectively. Song et al.[181] addressed the problem that inability of a lot of NNs to learn the spatial information of dense crowd motion, proposing a deep convolutional LSTM network to learn the interaction between the pedestrian and the environment, which is able to simulate more realistic motion trajectories of dense crowds such as evacuation and contraflow. Zhao et al.[182] presented a multi-feature fusion recursive NN by mapping preceding crowd states to causally consequent future states, which accurately reproduces the self-organization phenomenon in bidirectional crowds. Song et al.[183] constructed a four-layer neural network and train it with multiple scene data to generate pedestrian positions and velocities to simulate crowd movements in different scenarios. Compared with the traditional social force model, the mean square error of this model and the fluctuation of pedestrian position are smaller. Tkachuk et al.[184] accurately modeled crowd evacuation inside buildings in emergency situations based on a deep NN with several hidden layers and dropouts.

Microscopic data-driven methods learn behavioral features from real data and can present more realistic simulation results. However, they are limited by the sample database, and can only be processed well when there are similar samples. In addition, the efficiency of model learning and searching must be considered.

Macroscopic methods

Macroscopic data-driven methods adopt the velocity field, navigation field, vector field, optical flow, geometric flow, etc. to represent collective movement[185].

The main idea is to separate the original video into many frames arranged in chronological order and extract the velocity field from the successive frames. The environmental information of the simulated scene is compared with the environmental information in the video on a macroscopic level, and then the existing velocity field information is used to drive collective movement simulations. Musse et al.[186] captured crowd movement information based on video data of low-density scenes, and extract pedestrian motion trajectories to build an extrapolated velocity field. Later, some scholars conducted research on analyzing video data of high-density congested scenes. Zhong et al.[187] calculated velocity fields by combining offline and online videos to guide agents movement at the global level, where offline data can quickly capture pedestrian motion features and online data can refine motion details. Then, Zhong et al.[188] characterized the crowd behavior modeling problem as a symbolic regression problem, using a self-learning gene expression programming approach to automatically learn and generate behavior rules from crowd video data. Patile et al.[189] built velocity and navigation fields from real scene data to provide global preferred velocity for crowd movement.

In addition to the velocity field, researchers also propose navigation field, vector field, the optical flow and so on. Hu et al.[190] proposed optical flow method. This method employs motion flow fields instead of long-term motion tracks, and calculates flow vectors for each frame. Jin et al.[191] realized large-scale crowd navigation simulation in complex scenes using multiple vector fields. Wu et al.[192] constructed a conjugate field on the basis of the motion vector field, and these two fields describe tangential and radial motions, respectively. They also take the curl and scatter of motion trajectories into account to effectively simulate the human crowd movement behavior. Nayan et al.[193], building upon the research by Hu et al. [190], expanded the optical flow method to correlate the amplitude matrix of optical flow vectors. Khan[194] utilized optical flow and particle advection to extract crowd motion features assuming that pedestrians are not free and usually undergo lateral oscillations in high-density crowded environments.

Other researchers simulate collective movement from a geometric perspective. Lin et al.[195, 196] learnt crowd movement and generated the geometric flow instead of motion flow. In [195], integral motion was first captured through elementary geometric transformations, followed by the introduction of a Lie algebraic representation, which maps the transformation group to a vector space. In [196], the geometric flow of movement in space and time was described simultaneously, as well as a stochastic flow model incorporating Gaussian processes was built to simulate continuous motion in dynamic scenes. Based on this, Fan et al.[197] represented the vehicles movement as a set of geometric flows moving in the time direction.

Macroscopic data-driven methods learn global features (such as the velocity distribution in the current space) of collective movement from real data and are able to reproduce real and large-scale movements. The disadvantage is that the simulation result depends on the data quality, and the transferability and flexibility are poor.

Summary

In the above two types of methods, the data comes from the real world, so the simulation results are highly accurate. However, the focus of the two methods is different. Specifically, microscopic methods focus on learning behavioral features, and macroscopic methods focus on learning global features.

3.3.3 Dynamic adaptability

Dynamic adaptability refers to the self-adaptive ability of a method according to the environment. In the real world, the environment is constantly changing, which affects collective movements. Many scholars have noticed this property and proposed simulation methods with dynamic adaptability. These methods can be broadly classified into three categories: hybrid model-driven and data-driven, deep reinforcement learning and human-in-the-loop according to their different adjustive methods.

Hybrid model-driven and data-driven

By combining model-based methods and data-driven methods, the hybrid model-driven and data-driven methods are able to show mechanism descriptions and real results.

Scholars improved classical model-driven method based on real data. Rudloff et al.[198] calibrated a SFM depicting the boarding, alighting, and waiting behavior of pedestrians in a subway station based on measured data that incorporates pedestrian acceleration and desired velocity. Seer et al.[199] analyzed the depth data of crowd movements within a corridor captured by three Kinect sensors using a clustering approach and calibrate three improved SFM to promote collision avoidance behavior by adding relative velocities between individuals. Tang and Jia[200] adopted regression methods to process pedestrians trajectories data from real-world subway stations and use least squares to modify the SFM so that it can accurately reproduce the pedestrian flow characteristics in subway stations. Ko et al.[201] employed maximum likelihood estimation to construct a SFM based on observed pedestrian walking trajectory data. Seer et al.[202] analyzed real-world pedestrian data through a nonlinear regression-based approach to validate SFM and estimate its model parameters. Liu et al.[203] employed a maximum likelihood estimation method to estimate SFM parameters based on real road video data. Lovreglio et al.[204] calibrated different pedestrian models based on an open pedestrian trajectory dataset and proposed two FFCA models with Euclidean and modified Euclidean distance metrics.

Other researchers have calibrated the parameters of different models on real data. Lemercier et al.[205] presented a calibration of a pedestrian following model for simulating crowd queues. Anvari et al.[206] developed a microscopic model to simulate pedestrians and vehicles behavior, using an optimization algorithm to process empirical data and determine the interaction parameters of individuals. Zeng et al.[207] applied a genetic algorithm to evaluate the error between the model and actual data in terms of pedestrian flow, speed, acceleration, pedestrian-vehicle conflict and the lane formation phenomenon. Hussein and Sayed[208] presented a model for simulating the movement of pedestrians in a congested environment, in which a genetic algorithm is used to calibrate the model parameters. Bode[209] fitted model parameters based on data from a one-way crowd passing a bottleneck using the approximate Bayesian computation method. Liu et al.[210] proposed a velocity-based dynamic crowd movement simulation method to find the optimal velocity of agents from a real-world crowd velocity dataset.

Hybrid model-driven and data-driven methods can optimize their model parameters by multiple sets of high-quality data that match the simulation scenarios to maximize the benefits of the model. However, there is no solution to the limitations of the model itself (idealized assumptions).

Deep reinforcement learning methods

In collective movement simulations, deep learning methods allow learning potential movement features from high-dimensional data; reinforcement learning methods enable multi-agent to learn optimal movement strategies in the process of interacting with the environment[211]. Combining them, an agent is able to have both the understanding ability of deep learning and the decision-making ability of reinforcement learning, with the ability to better handle complex situations.

Many researchers have studied mobile robot navigation simulation. Kato et al.[212] in order to achieve adaptive navigation of a robot in a congested environment, combined local navigation based on DRL and global navigation based on topological maps. This method enables the robot to reach its destination while avoiding dynamic obstacles, but it is trained in a 2D simulator, which can speed up the learning time but has limitations with the real 3D environment. Therefore, Feng et al.[213] trained agents in a 3D simulator based on double deep Q network (DDQN) to achieve collision-free path planning for a mobile robot. Zhang et al.[214] presented a successor-feature-based reinforcement learning (DRL) for robots to quickly adapt to changing navigation targets and environments, which can transfer previously acquired navigation knowledge to new tasks. Hsu et al.[215] suggested a distributed DRL in different local regions, achieving indoor visual navigation in the large-scale environment without extra map information and human instruction.

Several scholars have focused on the navigation problems of unmanned aerial vehicles (UAVs), unmanned ground vehicles, etc. Wang et al.[216] argued that the UAV navigation problem in large-scale unknown complex environments is viewed as a partially observable Markov decision process (POMDP), and proposed a faster policy learning algorithm for POMDP based on actor-critic architecture. They advanced an online DRL algorithm to tackle the POMDP problem subsequently, which directly maps UAVs′ raw sensory measurements into control signals for navigation. This method is able to expand autonomous navigation of UAVs to more complex, large-scale 3D environment[217]. And then they adopted a Markov decision process with sparse rewards and put forward a non-expert-assisted DRL algorithm that ensures that the solution is not biased in a potentially suboptimal direction[218].

In addition, the DRL approach has been widely applied to crowd simulation. Xu et al.[219] integrated ORCA with the DRL method, proposing the ORCA-DRL local motion simulation method. This approach implements local collision avoidance by optimal reciprocal collision avoidance (ORCA) and trajectory smoothing by DRL. A deep neural network (DNN) is used for the agent state-action mapping and the DNN parameters are updated using proximal policy optimization based on the actor-critic. Subsequently, Xu et al.[220] introduced a multi-exit crowd evacuation simulation method based on DRL, called Multiexit-DRL. It employs a DNN to facilitate the mapping of agent states to actions and applies Rainbow DQN to enhance data utilization and algorithm stability, with movement space divided into eight isometric directions available to pedestrians. Zhu et al.[221] proposed a novel context-aware multiagent broad reinforcement learning method for simulating mixed pedestrian-vehicle traffic. Zhang et al.[222] came up with a data-driven crowd evacuation framework based on hierarchical DRL that allows for path planning and collision avoidance, respectively. Zhang et al.[223] refined human perception and behavioral decision strategies to reproduce the classical bottleneck effect along with pedestrian navigation.

The DRL methods adapt to the dynamic and complex environment. However, there are two problems. First, when the environment becomes complex, the number of interactions between the agent and the environment increases sharply, which requires a long training time. Second, because the data distribution between the virtual environment and the real environment is quite different, it is difficult to migrate from the virtual environment to the real environment.

Human in the loop

The human-in-the-loop approach is more worthy of investigation due to robustness and user preference considerations. Combining autonomy with user control, taking advantage of human-in-the-loop allows for higher-level task planning and control.

Concepts. The most common methods of sharing control between the user and autonomous system include two: control switching/division, and shared autonomy.

Control switching refers to discrete switching between full autonomy and direct control during the control process. Control switching depends on a predefined environment, and in each state, the robot evaluates whether to take over[224] or prevent the system from entering an unsafe state[225] based on the plausibility of the user′s intent inference.

Control division means that the human and autonomous system are each responsible for a part of the task and do not change dynamically. Simpson and Levine[226] proposed an adaptive approach for a shared control system that uses a Bayesian network to combine two adaptation mechanisms of user speed control and autonomous system direction control. Driessen et al.[227] divided the control space by placing end-effectors in the x-axis, y-axis, and z-axis directions, respectively, with the user to control the actuators in the z-axis and the system to control the x-axis and y-axis directions, thus forming a collaborative controller. While the control division approach clearly categorizes the tasks within the system, the responsibilities of humans and autonomous systems remain unchanged regardless of the environment. Therefore, it is not well applicable to complex, unknown, and dynamic environments.

The above approaches are often referred to as shared control, where a robot control framework is designed to achieve human-robot interaction, and the control between the human and the robot is constant unless manually adjusted by the human.

As sensing, reasoning, modeling, and learning methods continue to advance, the ability of shared control and its applications are expanding, called shared autonomy (SA). Shared autonomy strives to fuse human intent and autonomous system computation results with each other in a shared manner, avoiding the current problem of relying on one party entirely when human-robot decisions are inconsistent. Shared autonomy elevates the robot from a passive motion follower or actuator to a partner, leveraging the adaptability of human decision making in dynamic, uncertain environments and the robot's ability to automate. It is possible for a multi-agent system to automatically scale the level of autonomy based on internal or external (e.g., human, task, or environmental) information, eliminating the need for manual human adaptation and allowing better adaptation to the surrounding environment[228].

Shared autonomy strategy. The most critical issue in shared autonomy is the division of autonomy between human and autonomous systems. There are mainly two approaches to generate autonomy policies: arbitration methods and policy-based methods.

In arbitration methods, user behavior and full autonomy are considered as two independent sources, and the amount of mixture is usually determined using an arbitration function. Taking into account the dynamic complexities of the environment, it is necessary to assign different weights to the two distinct decision-making entities, humans and autonomous systems. Linear combination is one of the most common strategies. Jansen et al.[229] measured the trustworthiness of the user and the autonomous system considering the state of the environment, adopting a linear hybrid approach to obtain the final arbitration policy. Gopinath et al.[230] proposed a user-driven arbitration parameter optimization method based on optimal control theory, considering high user satisfaction, where the user adjusts the interaction parameters until their desired goal is reached, instead of using a standard nonlinear optimization algorithm. Oh et al.[231] suggested a natural gradient that allows shared autonomy to be described as an optimization problem. Shared actions are chosen to maximize the internal action value function of users while limiting the sharing policy to deviate from the autonomous robot policy. Xu et al.[232] dynamically scaled user arbitration weights by RL algorithms based on user control efficiency and walking environment. Reddy et al.[233] maximized task reward and user feedback rewards using DQN. Following on this, Schaff and Walter[234] expanded the approach by using residual policy learning to maximize human control authority. Oh et al.[235] employed a deep deterministic policy gradient approach based on RL methods to learn optimal arbitration policies from user interactions. It is possible to both assign more control for human and learn different preferences of different users, meanwhile allow the robot to complete control tasks in continuous action space.

The strategy-based approaches focus on the distribution of all targets and may help even when the confidence in predicting targets is relatively low. This is helpful in adapting to complex environments where it is difficult to predict a single goal in a cluttered environment. The core idea is to minimize the cost function of shared autonomy when the user goals are unknown. Hauser[236] minimized a distance-dependent cost function to reason about the goal distribution, and Javdani et al.[237] expanded on this by allowing the use of any cost function for which a value function is calculable. Their proposed framework is shown in Fig. 4, where u is user actions, a is a system action, and T is the transformation of the world from x to x'. When the system is unsure of a user's goal, it optimizes a secondary action that helps achieve many goals. And it focuses on specific goals when the system confidently predicts individual user goals. Reddy et al.[233] put forward a model-free deep reinforcement learning framework to assist users in tasks with unknown dynamics, user policies, and goals.

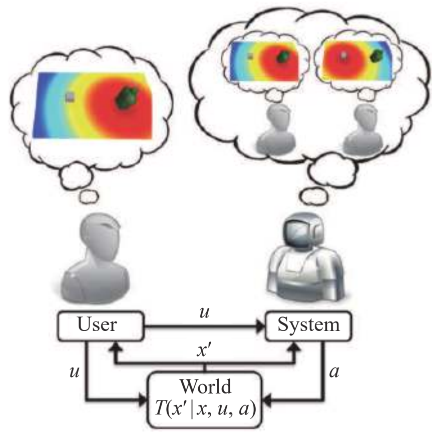

Fig. 4 Shared autonomy framework[237]

Human-in-the-loop methods take full advantage of human perception, decision-making, and operation. However, there are still challenges in judging whether human intervention is required, estimating the human internal state, evaluating whether human operations are correct, and effectively integrating instructions.

Summary

The above three kinds of methods have dynamic self-adaptive ability. Their differences consist in the way to achieve the adaptation, hybrid model-driven and data-driven by switching different methods/optimizing their model parameters, DRL by learning and exploration, and human-in-the-loop by human intelligence. And the adaptability of these three methods is incremental.

3.3.4 Assessment feedback capability

Assessment feedback capability refers to the ability of the methods that can give users some assessment feedback. The most significant assessment feedback capability is risk assessment. Risk assessment first assesses risks around an agent, and then makes sequential action decisions to avoid them[238, 239]. Risk assessment methods are classified into two categories, deterministic and probabilistic methods.

Deterministic methods use a rule-based expert system with simplified predictive models (constant yaw rate and acceleration) to calculate predetermined risk metrics (time interval, time to collision, braking time, stopping time, and reaction time) to determine whether a potential collision will occur[240, 241]. Among them, time to collision (TTC) is the most representative metric because this time-based metric physically reflects spatial distance and speed differences. In general, by the current state of the agents, the collision time can be derived by calculating the relative distance between two agents. Kim and Kum[240] predicted the future trajectory of surrounding vehicles by target lane detection to accurately calculate the collision time. Bošnak and Škrhanc[241] integrated laser ranging sensors with a moving system motion model and forecast the virtual paths of obstacles in the sensor′s local coordinate system. It avoids discretization of temporal or spatial prediction layers and estimates the collision time using analytical methods. None of these methods has a large computational burden and enables accurate collision risk assessment in simple scenarios. However, they perform poorly in more complex scenarios, fail to explicitly model the uncertainty of the input data, and inherently fail to reflect the uncertainty of future motion.

Probabilistic methods describe risk level by probability description. Noh and An[242] applied Bayesian models to combine conventional metrics into risk probability assessment and then developed rule-based expertise to control primary vehicles at intersections and on highways. Yu et al.[243] modeled vehicles as particles, and propagated the particles through their kinematics, by using the distribution of particles during propagation as the risk distribution for collision avoidance. Shin et al.[244] introduced vehicle-to-vehicle communication to predict remote vehicle locations with uncertainty and evaluate risk probabilities by the number of collisions within the uncertainty boundary. However, these methods do not take driver style preferences into account. Li et al.[245] proposed a probabilistic method for collision avoidance risk assessment that considers both driving safety and driver style preferences. For special crash scenarios, Shen et al.[246] used surrounding vehicle states (relative position, velocity, and acceleration) and a predictive occupancy map algorithm for side and rear-end collision scenarios. Intersections are high risk areas, and Deveaux et al.[247] presented a risk metric applicable to crossings and allowed for dynamic adjustment of risk thresholds based on driver style. Zhu et al.[248] proposed a method that combines supervised learning and Bayesian hierarchical models, which predict the probability at different risk levels.

Assessment feedback capability allows real-time quantitative analysis and provides a flexible, dynamic feedback for simulation. It is a promising work to construct an objective, structured, and comprehensive assessment feedback framework.

3.4 Summary

A comparison among four categories of collective movement simulation methods is presented in Table 2. In order to help users to find a type of method that can meet their specific applications, we summarize the above methods according to their collective types, scales, individual behavior descriptions, input data and pre-training.

Tables 3–6 successively shows some collective simulation methods for the type of human crowds, vehicles, pedestrian-vehicles, and robots successively. The collective scale describes how many individuals that the methods can calculate in general. The limited scale refers to the number of individuals less than 500, and the large-scale refers to the number of individuals from 500 to 1 000, or even more[19]. The data-driven describes whether the methods need datasets for learning, and the pre-training means whether there are pre-trainings for the methods before applications.

Specifically, as the highest intelligence on earth, humans have rich collective types and individual behaviors. As shown in Table 3, crowds present collective types such as queuing, grouping, confrontation, etc., and individuals also have diverse behaviors in terms of personality, emotion, physiology and psychology, etc. The movements of vehicles are always lane-based, showing collective types such as car-following and lane-changing. Their movements are closely related to the individual behavior of the driver. As seen in Table 4, researchers have paid attention to the effects of driver style, preference, cognition and so on. In addition, traffic is a complex scenario with multiple traffic participants, of which pedestrian-vehicle is a typical heterogeneous interaction. As shown in Table 5, pedestrian-vehicle interactions mainly occur in crossings. For robots, the research focuses on their navigation in complex environments, as shown in Table 6, which mainly includes 2D and 3D environments.

Table 2 Characteristics of collective movement simulation methods

	Technical objectives	Advantages	Disadvantages	Methods contain	Typical work
Versatility	Mechanism description	Universal; Transfer to other similar scenes	Not real	Microscopic models	Rule-based model[11,12,123,124], Cellular automata model[127–143], Social force model[105,144–151], Continuous model[153–161], Potential field model[162–169]
Accuracy	Reconstruct real scenes	Vivid results	Need data; Poor transformation performance	Microscopic data-driven	Lee et al.[172], Bi et al.[175], Wei et al.[176], Zhao et al.[182], etc.
				Macroscopic data-driven	Musse et al.[186], Jin et al.[191], Lin et al.[195, 196], Fan et al.[197], etc.
Dynamic adaptability	Transfer to other scenes	Excellent transformation performance	Immature method	Hybrid driven	Seer et al.[199], Rudloff et al.[198], Ko et al.[201], Bode[209], etc.
				Deep reinforcement learning	Kato et al.[212], Zhang et al.[214], Zhang et al.[223], etc.
				Human in the loop	Jansen et al.[229], Oh et al.[231], Xu et al.[232], Reddy et al.[233], etc.
Assessment feedback capability	Quantitative results	Flexible assessment criteria	Including subjective factor	Deterministic methods	Kim and Kum[240], Bošnak and Skrjanc[241], etc.
				Probabilistic methods	Noh and An[242], Yu et al.[243], Shin et al.[244], Li et al.[245], etc.

Table 3 Characteristics of crowd simulation methods

Collective scale	Collective type	Individual behavior	Data-driven	Pre-training	Reference
Limited scale	–	Personality, psychology	No	No	[143, 154, 155]
	–	–	No	No	[131–136, 144–147]
	–	–	No	Yes	[219, 220, 223]
	–	–	Hybrid	No	[198–201]
	–	–	Yes	Yes	[181–184]
	–	Physiology and psychology	Yes	Yes	[177]
	Queuing	Emotion	No	Yes	[81]
	Queuing	Following	Hybrid	No	[208]
	Group	Friends, Families	No	No	[133]
	Confrontation	Emotion	No	No	[82, 83]
Large scale	–	–	No	No	[156–159, 161]
	–	–	Yes	No	[189, 191, 196]
	–	–	Yes	Yes	[192–195]

Table 4 Characteristics of vehicles simulation methods

Scenario	Collective scale	Collective type	Individual behavior	Data-driven	Pre-training	Reference
Lane-based	Large scale	Car-following	–	No	No	[153, 155, 160]
	Limited scale		–	Yes	No	[190, 197]
			–	No	No	[127, 128, 137]
			–	Yes	Yes	[170, 174]
	Limited scale	Lane-changing	–	No	No	[138, 139, 240, 241]
			–	Yes	Yes	[179, 180]
			Cognitive psychology	No	No	[92]
			Driver preferences	No	No	[245]
			Driver state	No	No	[94–99]
Crossing	Limited scale	–	–	No	No	[242]
			Driver preferences	No	No	[247]

Table 5 Characteristics of pedestrian-vehicle simulation methods

Scenario	Data-driven	Pre-training	Reference
Crossing	No	No	[148, 149]
Crossing	Yes	Yes	[175]
Crosswalk	Hybrid	No	[203]
Street	Hybrid	No	[112, 204]

Table 6 Characteristics of robots simulation methods

Scenario	Data-driven	Pre-training	Reference
2D	No	No	[163]
	No	Yes	[212, 229, 234]
3D	No	No	[86, 88, 90, 91, 164, 169]
	No	Yes	[213–215, 217, 218, 230–233, 235–237]

4 Applications

Collective movement simulation technology has been extensively used in layout optimization, emergency control, dispatching, unmanned systems, and other derivative applications.

4.1 Layout optimization

The collective movement is closely related to the layout of buildings. A reasonable layout will bring users a satisfactory and comfortable experience. Otherwise, it may lead to a decrease in the utilization of facilities and even cause certain safety hazards. In particular, railway stations, parks, squares, shopping centers, traffic roads, etc. Therefore, the evaluation and optimization of the comfort, usability, and functionality of buildings based on collective movement simulation technology from the perspective of the users have become a key step in the fields of ship construction, building design, and infrastructure construction[249, 250].

The simulation results of collective movement assist architects or related experts to make informed design decisions that improve both building utilization and user comfort. Aschwanden et al.[250] incorporated a parametric approach with an agent-based model to simulate the behavior of residents in an urban environment to further optimize the efficiency of public transportation and the availability of convenient facilities. Mathew et al.[251] improved the structure of urban traffic walkability through interactive design. Feng et al.[252] trained nonlinear regressors through a data-driven approach to mine the relationship between crowd attributes (mobility, accessibility, and comfort) and the geometric features of the layout. It synthesizes crowd-aware layouts to improve layouts with better crowd flow characteristics. Khamis et al.[253] merged collective simulation models with multi-objective optimization techniques to evaluate and optimize plant layout. It promotes worker productivity while ensuring their life safety. In addition, Garcia-Dorado et al.[254] advanced an interactive method in which the designer displays the specified desired vehicle traffic behavior (lane occupancy, travel time, emissions), and the system automatically calculates a 3D urban traffic models (road networks, neighborhoods). Haworth et al.[255] optimized the design, by simulating the effect of newly added environmental elements (columns, doors, passageways) on crowd movement and feeding back to the designer with aggregate statistics and heatmaps. This system permits the designer to iteratively improve the design solution, while also specifying different crowd configurations. Chakraborty et al.[256] argued that small changes in environmental design may affect crowd motion in unexpected ways and use crowdsourcing techniques to integrate the wisdom of users (ordinary experiencers and experts) within a gamified collaborative design framework. Users propose designs based on computer simulations and receive feedback from other users to quickly update their designs.

4.2 Emergency control

Crowd evacuation efficiency is significantly related to the public safety of the humans. An efficient evacuation plan leads humans out of the danger zone in the shortest possible time. In contrast, it may cause more adverse effects. Therefore, crowd evacuation simulation in emergency situations is able to optimize evacuation plans, and improve emergency management measures in public places[24, 257].

Several scholars have studied crowd evacuation based on place types, such as airports, shopping centers, and school buildings. Tsai et al.[258] believed that there are four distinctive features of airport evacuations: first, there are many different types of agents, such as families (parents, children) and first-time visitors; second, emotional interactions, children tend to turn towards their parents; third, information interactions, tourists rely on signage indicating exits; and fourth, behavioral interactions, the number of human collisions increases as panic spreads. Therefore, they propose a multi-agent evacuation simulation method for simulating crowd escape behavior in airport terminals to provide specific recommendations to the security department. Tan et al.[259] presented an agent-based model for building evacuation and evaluate its impact on evacuation efficiency by considering individuals' estimation of feasible space and knowledge of firefighting facilities. Wong et al.[260] calculated the optimal path for each local area within a building, aiming to complete crowd evacuation quickly and reduce congestion while maximizing the number of humans reaching the exit. This method determines the optimal path considering crowd distribution, exit location and corridor width, etc. Zang et al.[261] studied the impact of obstacles (desks, benches, podiums) on crowd evacuation in a high-rise school building, as well as point out that a standardized evacuation order and reasonable desk arrangement.

Other researchers start from the types of emergencies, such as earthquakes, fires, and tsunamis, etc. Lu et al.[262] quantified the impact of debris falling during earthquakes on crowd evacuation. Wang and Jia[263] proposed a multi-modal personnel evacuation model considering the speed-adjusted behavior of pedestrians and multiple escape modes (walking, by car) in a tsunami. In addition to sudden emergency safety events, the spread of epidemic diseases also affects the health of humans. Lv et al.[264] established an agent-based infection model with mean-field theory, proposing a simulation model of campus virus infection and control. This model simulates the probability of virus transmission in a dense population, which facilitates the development of reasonable prevention and control measures to reduce the risk of disease transmission.

4.3 Dispatch and schedule

There are many scheduling problems in real life, such as logistics scheduling problems[265], and traffic scheduling problems like signal control[266]. Collective movement simulations have become the main solution to these problems.

Logistics scheduling is a highly complex system, in which a favorable scheduling scheme leads to efficient and fast transportation. Otherwise, it will reduce the efficiency of logistics and transportation, and even cause safety problems. Simulation techniques are available to evaluate or optimize scheduling schemes in advance for efficient production. The container terminal system was modeled using an agent-based method, aiming to improve its scheduling and decision making[267]. Elia et al.[268] presented a hybrid simulation model aimed at improving the efficiency of garbage collection services, and proposed a hybrid scheduling scheme that improves truck utilization while flexibly meeting customer demand.

The traffic congestion problem of the current urban road network is becoming more and more serious. By optimizing the traffic efficiency, fuel consumption and safety indicators, the service performance of the road can be improved and the probability of accidents can be reduced[269]. Kamal et al.[270] suggested a vehicle coordination scheme for unsignalized intersections, which calculates the optimal vehicle trajectory by avoiding the risk of collision near the intersection and minimizing the occurrence of conflicts. Moradi-Pari et al.[271] adopted a dynamics model for large-scale networked vehicles to depict their basic motions (braking, acceleration). This method describes the following, steering and other movements of vehicles, realizes multi-vehicle coordination, and improves road network capacity. Zhang et al.[266] proposed a traffic signal scheduling strategy for pedestrian-vehicle mixed-flow networks. With the integration of the pedestrian-vehicle model, the traffic light performance is investigated to provide convenience to pedestrians and reduce delays for both vehicles. Then, Zhang et al.[272] put forward a new traffic signal scheduling strategy for urban traffic networks to address the problem of pedestrians who are unable to cross crosswalks within the specified time due to violations.

4.4 Unmanned systems

With the continuous development of intelligent devices, unmanned vehicles, UAVs, and other unmanned systems are increasingly used in the real world using existing collective intelligence.

The cooperative control of unmanned systems is the most direct application of collective intelligence[273, 274]. Das et al.[275] used an improved gravitational search algorithm to achieve the coordination of multi-robots, so that they could cooperate with each other to accomplish a common goal in a cluttered environment. For tackling the formation control of unmanned systems, Zhao and Ma[276] developed a path-following guidance system based on a virtual leader, which enables unmanned surface vessels (USVs) to maintain a well-formed formation, and Jin et al.[277] proposed a distributed soft formation control strategy, achieving formation collision avoidance with local observations under dynamic environmental disturbances, which can easily adapt to changes in the formation shape and size throughout the mission process. For addressing path planning problem of multi-UAVs, Shi et al.[278] proposed the multiple swarm drosophila optimization algorithm achieving information exchange and collision avoidance, De Alcantara Andrade et al.[279] raised the particle swarm optimization algorithm for multiple UAVs during search and rescue missions. For solving target tracking of multi-UAVs in urban environment, Yao et al.[280] proposed a hybrid algorithm combining model predictive control and an improved gray wolf optimizer, Wu et al.[281] suggested a distributed model based on the adaptive locust optimization algorithm, and Wang et al.[282] advanced an improved gray wolf optimization algorithm using a distributed Gaussian estimation strategy.

4.5 Derivative applications

In addition to the above applications, there are other derived applications to solve complex combinatorial optimization problems, like traveling salesman problem (TSP)[283], social platform supervision[284], financial computing[285], and electronic power systems[286].

The TSP problem is a classical combinatorial optimization problem with a wide range of applications, like transportation, circuit board design, etc. Dorigo et al.[14] put forward an ant colony optimization algorithm to solve the TSP problem, which pioneers the application of biological intelligence to solve combinatorial optimization problems. Ouaarab et al.[287] used an improved discrete cuckoo search algorithm in which local perturbations are introduced to increase the flexibility of solving the TSP problem. Osaba et al.[288] solved symmetric and asymmetric TSP problems using a discrete bat algorithm. Huang et al.[289] addressed the TSP problem using a discrete shuffled frog-leaping algorithm, which not only yields a higher accuracy solution but also has good stability.

Social platform supervision often uses manual auditing to remove undesirable content, etc. With the growth of collaborative collective intelligence algorithms, more and more social platforms are applying them to improve the supervision methods. Roaming bots in Wikipedia[290], which are able to perform tasks such as supervising website content, merging similar knowledge entries, splitting complex work, and closing glitches[291], play an important role in the process of knowledge editing.

Furthermore, in economic finance, Shi et al.[292] developed appropriate insurance investment plans using data-driven models and distribution estimation algorithms. In power systems, particle swarm algorithms provide solutions to different applications of power system optimization problems[286]. In aerospace, Asafuddoula et al.[293] researched spacecraft design problems using decomposition-based evolutionary algorithms, and Wang et al.[294] improved particle swarm optimization algorithms based on active learning for wing design optimization problems. In biomedicine, Fjell et al.[295] applied genetic algorithms for the identification of antimicrobial peptides to improve identification efficiency.

5 Conclusions and future work

This paper reviews the methods in collective movement simulations. Some confusing concepts are clarified, and methods are classified according to objects, fields, and effects, so as to facilitate users to make correct choices. In addition, this paper summarizes the application of collective movement simulations in layout optimization, emergency control, dispatching, unmanned systems and other derived applications.

In terms of collective movement simulation methods themselves, here we discuss the following five future directions.

Explainable data-driven methods. Existing data-driven collective simulation methods have achieved good results in simulating collective movements. However, these methods usually rely on large amounts of perfect data. The transferability and robustness of these methods are generally poor. How to learn and explore the essence of collective movements based on existing data is a topic worthy of research.

Intersections between individual behavior model and collective movement models. Many Individual behavior factors, such as personality, culture, emotion, sociality and politics, affect collective movements. At present, individual behavior models are mainly from the life science field. Their computational efficiency is usually low. How to integrate these individual behavior models with existing collective movement models to realize large-scale collective movement simulations efficiently is a promising research topic.

Intersections between collective movement models. Scholars in mathematics, physics and information field have developed various kinds of collective movement models. The outputs of these models are similar, but each has its own advantages and disadvantages. How to integrate the above methods and interactively optimize them to realize simulations effectively is one of the topics worth studying.

Simulation evaluation. In recent years, collective movement simulation methods have proliferated. However, there are relatively few studies on model evaluations. In fact, realism and accuracy are key concerns when users want to use collective movement simulation methods. Therefore, how to quantitatively and systematically evaluate existing methods is a direction worth investigating

Human-in-the-loop simulation. Machine intelligence is limited, and mathematical models cannot simulate all phenomena in detail. In recent years, the human-in-the-loop approach has attracted the attention of many scholars, interacting with users during the simulation process, and performing user-editable simulations, such as real-time adjustment of environmental parameters, agent states, etc. However, there is still a lot of work. For example, when humans need to participate in a simulation? How to integrate human intelligence into the machine intelligence?

In terms of the applications of collective movement simulation methods, here we discuss the following two points.

Co-optimization between collective movement methods and their applications. More and more scholars and industry experts consider collective movement simulations as an inseparable sub-part of layout optimization, emergency control, scheduling optimization. There has been lots of work on the use of collective movement (such as human and vehicles) simulation in these applications. However, there are still few co-optimization methods for collective movement and the applications, which is important for decision-making and control. How to combine the existing collective movement simulation methods with layout optimization, emergency control and scheduling algorithms to realize a co-optimization is worthy of further research.

Human-in-the-loop digital twins. The collective movement behavior exists widely in various digital twin systems. At present, scholars generally use digital twins by integrating collective movement methods. How to realize iterative optimization between collective movement and other functional modules or the actual physical world, and how to fully integrate human (user) intelligence into the optimization, still need to be further researched by scholars in the fields of life science, mathematics, physics and information science.

Acknowledgements

This work was supported and funded by National Natural Science Foundation of China (Nos. 62072415 and 62036010), the National Key Research and Development Program of China (No. 2021YFB3301504), the Natural Science Foundation of Henan Province, China (No. 202300410496), the China Postdoctoral Science Foundation (No. 2019MM662530), the Special Project for COVID-19 Prevention and Control Emergency Tackling of Henan Science and Technology Department, China (No. 201100312000), the National Defense Basic Scientific Research, China (No. JCKY2020XXXB028), and the Social Simulator (Zhengzhou) Major Science and Technology Infrastructure Construction Strategy Research, China (No. 2021HENZDA03).

Declarations of conflict of Interest

The authors declared that they have no conflicts of interest to this work.

References

[1] R. S. Parpinelli, H. S. Lopes. New inspirations in swarm intelligence: A survey. *International Journal of Bio-inspired Computation*, vol. 3, no. 1, pp. 1–16, 2011. DOI: 10.1504/ijbic.2011.038700.

[2] T. Vicsek, A. Zafeiris. Collective motion. *Physics Reports*, vol. 517, no. 3–4, pp. 71–140, 2012. DOI: 10.1016/j.physrep.2012.03.004.

[3] A. Strandburg-Peshkin, D. R. Farine, I. D. Couzin, M. C. Crofoot. Shared decision-making drives collective movement in wild baboons. *Science*, vol. 348, no. 6241, pp. 1358–1361, 2015. DOI: 10.1126/science.aaa5099.

[4] A. John, A. Schadschneider, D. Chowdhury, K. Nishinari. Trafficlike collective movement of ants on trails: Absence of a jammed phase. *Physical Review Letters*, vol. 102, no. 10, Article number 108001, 2009. DOI: 10.1103/PhysRevLett.102.108001.

[5] G. Andrienko, N. Andrienko, G. Fuchs, J. Wood. Revealing patterns and trends of mass mobility through spatial and temporal abstraction of origin-destination movement data. *IEEE Transactions on Visualization and Computer Graphics*, vol. 23, no. 9, pp. 2120–2136, 2017. DOI: 10.1109/TVCG.2016.2616404.

[6] M. L. Xu, Y. P. Wu, Y. D. Ye, I. Farkas, H. Jiang, Z. G. Deng. Collective crowd formation transform with mutual information-based runtime feedback. *Computer Graphics Forum*, vol. 34, no. 1, pp. 60–73, 2015. DOI: 10.1111/cgf.12459.

[7] I. Navarro, F. Matía. A framework for the collective movement of mobile robots based on distributed decisions. *Robotics and Autonomous Systems*, vol. 59, no. 10, pp. 685–697, 2011. DOI: 10.1016/j.robot.2011.05.001.

[8] M. Del Mar Delgado, M. Miranda, S. J. Alvarez, E. Gurarie, W. F. Fagan, V. Penteriani, A. Di Virgilio, J. M. Morales. The importance of individual variation in the dynamics of animal collective movements. *Philosophical Transactions of the Royal Society B: Biological Sciences*, vol. 373, no. 1746, Article number 20170008, 2018. DOI: 10.1098/rstb.2017.0008.

[9] L. Gibelli, N. Bellomo. *Crowd Dynamics, Volume 1: Theory, Models, and Safety Problems*, Cham, Switzerland: Springer, 2018.

[10] R. Eberhart, J. Kennedy. A new optimizer using particle swarm theory. In *Proceedings of the 6th International Symposium on Micro Machine and Human Science*, IEEE, Nagoya, Japan, pp. 39–43, 1995. DOI: 10.1109/MHS.1995.494215.

[11] C. W. Reynolds. Flocks, herds and schools: A distributed behavioral model. In *Proceedings of the 14th Annual Conference on Computer Graphics and Interactive Techniques*, ACM, Anaheim, USA, pp. 25–34, 1987. DOI: 10.1145/37401.37406.

[12] X. Y. Tu, D. Terzopoulos. Artificial fishes: Physics, locomotion, perception, behavior. In *Proceedings of the 21st Annual Conference on Computer Graphics and Interactive Techniques*, ACM, Orlando, USA, pp. 43–50, 1994. DOI: 10.1145/192161.192170.

[13] D. Karaboga. An Idea Based on Honey Bee Swarm for Numerical Optimization, Technical Report TR06, Computer Engineering Department, Engineering Faculty, Erciyes University, Kayseri, Turkey, 2005.

[14] M. Dorigo, V. Maniezzo, A. Colorni. Ant system: Optimization by a colony of cooperating agents. *IEEE Transactions on Systems, Man, and Cybernetics – Part B*, vol. 26, no. 1, pp. 29–41, 1996. DOI: 10.1109/3477.484436.

[15] Z. Han, A. L. Swindlehurst, K. J. R. Liu. Optimization of MANET connectivity via smart deployment/movement of unmanned air vehicles. *IEEE Transactions on Vehicular Technology*, vol. 58, no. 7, pp. 3533–3546, 2009. DOI: 10.1109/TVT.2009.2015953.

[16] M. Rubenstein, A. Cornejo, R. Nagpal. Programmable self-assembly in a thousand-robot swarm. *Science*, vol. 345, no. 6198, pp. 795–799, 2014. DOI: 10.1126/science.1254295.

[17] S. Mariani, F. Zambonelli. Degrees of autonomy in coordinating collectives of self-driving vehicles. In *Proceedings of the 9th International Symposium on Leveraging Applications of Formal Methods*, Springer, Rhodes, Greece, pp. 189–204, 2020. DOI: 10.1007/978-3-030-61470-6_12.

[18] K. Guo, H. Guan. Modelling of driver/vehicle directional control system. *Vehicle System Dynamics*, vol. 22, no. 3–4, pp. 141–184, 1993. DOI: 10.1080/00423119308969025.

[19] S. W. Yang, T. R. Li, X. Gong, B. Peng, J. Hu. A review on crowd simulation and modeling. *Graphical Models*, vol. 111, Article number 101081, 2020. DOI: 10.1016/j.gmod.2020.101081.

[20] Q. W. Chao, H. K. Bi, W. Z. Li, T. L. Mao, Z. Q. Wang, M. C. Lin, Z. G. Deng. A survey on visual traffic simulation: Models, evaluations, and applications in autonomous driving. *Computer Graphics Forum*, vol. 39, no. 1, pp. 287–308, 2020. DOI: 10.1111/cgf.13803.

[21] S. J. Chung, A. A. Paranjape, P. Dames, S. J. Shen, V. Kumar. A survey on aerial swarm robotics. *IEEE Transactions on Robotics*, vol. 34, no. 4, pp. 837–855, 2018. DOI: 10.1109/TRO.2018.2857475.

[22] A. Chakraborty, A. K. Kar. Swarm Intelligence: A review of algorithms. *Nature-inspired Computing and Optimization: Theory and Applications*, S. Patnaik, X. S. Yang, K. Nakamatsu, Eds., Cham, Switzerland: Springer, pp. 475–494, 2017.

[23] F. Martinez-Gil, M. Lozano, I. García-Fernández, F. Fernández. Modeling, evaluation, and scale on artificial pedestrians: A literature review. *ACM Computing Surveys*, vol. 50, no. 5, Article number 72, 2018. DOI: 10.1145/3117808.

[24] M. L. Xu, H. Jiang, X. G. Jin, Z. G. Deng. Crowd simulation and its applications: Recent advances. *Journal of Computer Science and Technology*, vol. 29, no. 5, pp. 799–811, 2014. DOI: 10.1007/s11390-014-1469-y.

[25] Y. Li, M. Y. Chen, Z. Dou, X. P. Zheng, Y. Cheng, A. Mebarki. A review of cellular automata models for crowd evacuation. *Physica A: Statistical Mechanics and its Applications*, vol. 526, Article number 120752, 2019. DOI: 10.1016/j.physa.2019.03.117.

[26] C. Kownacki, D. Ołdziej. Flocking algorithm for fixed-wing unmanned aerial vehicles. In *Proceedings of the 3rd Advances in Aerospace Guidance, Navigation and Control*, Springer, Toulouse, French, pp. 415-431, 2015.

[27] S. Z. Qu, M. Abouheaf, W. Gueaieb, D. Spinello. An adaptive fuzzy reinforcement learning cooperative approach for the autonomous control of flock systems. In *Proceedings of IEEE International Conference on Robotics and Automation*, Xi'an, China, pp. 8927–8933, 2021. DOI: 10.1109/ICRA48506.2021.9561204.

[28] R. Olfati-Saber. Flocking for multi-agent dynamic systems: Algorithms and theory. *IEEE Transactions on Automatic Control*, vol. 51, no. 3, pp. 401–420, 2006. DOI: 10.1109/TAC.2005.864190.

[29] M. M. Millonas. Swarms, phase transitions, and collective intelligence, [Online], Available: https://arxiv.org/abs/adap-org/9306002, 1993.

[30] J. Kennedy, R. Eberhart. Particle swarm optimization. In *Proceedings of ICNN'95-International Conference on Neural Networks*, IEEE, Perth, Australia, pp. 1942–1948, 1995. DOI: 10.1109/ICNN.1995.488968.

[31] E. Bonabeau, G. Theraulaz, M. Dorigo, G. Theraulaz. *Swarm Intelligence: From Natural to Artificial Systems*, New York, USA: Oxford University Press, 1999.

[32] A. Y. Zomaya. *Handbook of Nature-Inspired and Innovative Computing: Integrating Classical Models with Emerging Technologies*, New York, USA: Springer, 2006.

[33] C. Blum, D. Merkle. *Swarm Intelligence: Introduction and Applications*, Berlin, Germany: Springer, 2008.

[34] L. F. Henderson. On the fluid mechanics of human crowd motion. *Transportation Research*, vol. 8, no. 6, pp. 509–515, 1974. DOI: 10.1016/0041-1647(74)90027-6.

[35] M. Moussaid, S. Garnier, G. Theraulaz, D. Helbing. Collective information processing and pattern formation in swarms, flocks, and crowds. *Topics in Cognitive Science*, vol. 1, no. 3, pp. 469–497, 2009. DOI: 10.1111/j.1756-8765.2009.01028.x.

[36] L. F. Henderson, D. J. Lyons. Sexual differences in human crowd motion. *Nature*, vol. 240, no. 5380, pp. 353–355, 1972. DOI: 10.1038/240353a0.

[37] I. Karamouzas, M. Overmars. Simulating the local behaviour of small pedestrian groups. In *Proceedings of the 17th ACM Symposium on Virtual Reality Software and Technology*, ACM, Hong Kong, China, pp. 183–190, 2010. DOI: 10.1145/1889863.1889906.

[38] M. Moussaïd, N. Perozo, S. Garnier, D. Helbing, G. Theraulaz. The walking behaviour of pedestrian social groups and its impact on crowd dynamics. *PLoS One*, vol. 5, no. 4, Article number e10047, 2010. DOI: 10.1371/journal.pone.0010047.

[39] Z. Ren, P. Charalambous, J. Bruneau, Q. Peng, J. Pettré. Group modeling: A unified velocity-based approach. *Computer Graphics Forum*, vol. 36, no. 8, pp. 45–56, 2017. DOI: 10.1111/cgf.12993.

[40] T. Vicsek, A. Czirók, E. Ben-Jacob, I. Cohen, O. Shochet. Novel type of phase transition in a system of self-driven particles. *Physical Review Letters*, vol. 75, no. 6, pp. 1226–1229, 1995. DOI: 10.1103/PhysRevLett.75.1226.

[41] D. Helbing. Traffic and related self-driven many-particle systems. *Reviews of Modern Physics*, vol. 73, no. 4, pp. 1067–1141, 2001. DOI: 10.1103/RevModPhys.73.1067.

[42] D. Helbing. Collective phenomena and states in traffic and self-driven many-particle systems. *Computational Materials Science*, vol. 30, no. 1–2, pp. 180–187, 2004. DOI: 10.1016/j.commatsci.2004.01.026.

[43] D. Helbing, I. Farkas, T. Vicsek. Simulating dynamical features of escape panic. *Nature*, vol. 407, no. 6803, pp. 487–490, 2000. DOI: 10.1038/35035023.

[44] R. S. Crutchfield. Conformity and character. *American Psychologist*, vol. 10, no. 5, pp. 191–198, 1955. DOI: 10.1037/h0040237.

[45] X. T. Li, J. Zhang, M. H. Yin. Animal migration optimization: An optimization algorithm inspired by animal migration behavior. *Neural Computing and Applications*, vol. 24, no. 7, pp. 1867–1877, 2014. DOI: 10.1007/s00521-013-1433-8.

[46] X. S. Yang. *Nature-inspired Metaheuristic Algorithms*, Frome, UK: Luniver Press, 2010.

[47] S. Mirjalili, A. Lewis. The whale optimization algorithm. *Advances in Engineering Software*, vol. 95, pp. 51–67, 2016. DOI: 10.1016/j.advengsoft.2016.01.008.

[48] C. W. Reynolds. Steering behaviors for autonomous characters. In *Proceedings of Game Developers Conference*, San Jose, USA, pp. 763–782, 1999.

[49] D. Helbing, L. Buzna, A. Johansson, T. Werner. Self-organized pedestrian crowd dynamics: Experiments, simulations, and design solutions. *Transportation Science*, vol. 39, no. 1, pp. 1–24, 2005. DOI: 10.1287/trsc.1040.0108.

[50] J. A. Sokolowski, C. M. Banks. *Principles of Modeling and Simulation: A Multidisciplinary Approach*, Hoboken, USA: John Wiley & Sons, 2011.

[51] P. A. Fishwick. *Simulation Model Design and Execution: Building Digital Worlds*, New Jersey, USA: Prentice Hall PTR, 1995.

[52] J. Banks. *Handbook of Simulation: Principles, Methodology, Advances, Applications, and Practice*, New York, USA: John Wiley & Sons, 1998.

[53] J. Kennedy, R. C. Eberhart, Y. H. Shi. *Swarm Intelligence*, San Francisco, USA: Morgan Kaufmann Publishers, 2001.

[54] S. L. Lima, L. M. Dill. Behavioral decisions made under the risk of predation: A review and prospectus. *Canadian Journal of Zoology*, vol. 68, no. 4, pp. 619–640, 1990. DOI: 10.1139/z90-092.

[55] J. Krause, G. D. Ruxton. *Living in Groups*, Oxford, USA: Oxford University Press, 2002.

[56] G. Beauchamp. The effect of group size on mean food intake rate in birds. *Biological Reviews*, vol. 73, no. 4, pp. 449–472, 1998. DOI: 10.1111/j.1469-185X.1998.tb00179.x.

[57] B. L. Partridge, T. J. Pitcher. The sensory basis of fish schools: Relative roles of lateral line and vision. *Journal of Comparative Physiology*, vol. 135, no. 4, pp. 315–325, 1980. DOI: 10.1007/BF00657647.

[58] A. Huth, C. Wissel. The simulation of the movement of fish schools. *Journal of Theoretical Biology*, vol. 156, no. 3, pp. 365–385, 1992. DOI: 10.1016/S0022-5193(05)80681-2.

[59] J. L. Deneubourg, J. M. Pasteels, J. C. Verhaeghe. Probabilistic behaviour in ants: A strategy of errors? *Journal of Theoretical Biology*, vol. 105, no. 2, pp. 259–271, 1983. DOI: 10.1016/S0022-5193(83)80007-1.

[60] J. L. Deneubourg, S. Goss. Collective patterns and decision-making. *Ethology Ecology & Evolution*, vol. 1, no. 4, pp. 295–311, 1989. DOI: 10.1080/08927014.1989.9525500.

[61] S. Goss, R. Beckers, J. L. Deneubourg, S. Aron, J. M. Pasteels. How trail laying and trail following can solve foraging problems for ant colonies. In *Proceedings of Behavioural Mechanisms of Food Selection*, Springer, Berlin Heidelberg Germany, pp. 661-678, 1990.

[62] D. R. MacNulty, L. D. Mech, D. W. Smith. A proposed ethogram of large-carnivore predatory behavior, exemplified by the wolf. *Journal of Mammalogy*, vol. 88, no. 3, pp. 595–605, 2007. DOI: 10.1644/06-MAMM-A-119R1.1.

[63] K. Von Frisch. *The Dance Language and Orientation of Bees*, Cambridge, UK: Harvard University Press, 1993.

[64] J. C. Biesmeijer, T. D. Seeley. The use of waggle dance information by honey bees throughout their foraging careers. *Behavioral Ecology and Sociobiology*, vol. 59, no. 1, pp. 133–142, 2005. DOI: 10.1007/s00265-005-0019-6.

[65] B. Granovskiy, T. Latty, M. Duncan, D. J. T. Sumpter, M. Beekman. How dancing honey bees keep track of changes: The role of inspector bees. *Behavioral Ecology*, vol. 23, no. 3, pp. 588–596, 2012. DOI: 10.1093/beheco/ars002.

[66] H. C. Berg. Motile behavior of bacteria. *Physics Today*, vol. 53, no. 1, pp. 24–29, 2000. DOI: 10.1063/1.882934.

[67] B. Khelifa, M. R. Laouar. A holonic intelligent decision support system for urban project planning by ant colony optimization algorithm. *Applied Soft Computing*, vol. 96, Article number 106621, 2020. DOI: 10.1016/j.asoc.2020.106621.

[68] H. T. Zhao, C. S. Zhang, X. Y. Zheng, C. Zhang, B. Zhang. A decomposition-based many-objective ant colony optimization algorithm with adaptive solution construction and selection approaches. *Swarm and Evolutionary Computation*, vol. 68, Article number 100977, 2022. DOI: 10.1016/j.swevo.2021.100977.

[69] Y. Wang, L. Wang, G. C. Chen, Z. Q. Cai, Y. Q. Zhou, L. N. Xing. An improved ant colony optimization algorithm to the periodic vehicle routing problem with time window and service choice. *Swarm and Evolutionary Computation*, vol. 55, Article number 100675, 2020. DOI: 10.1016/j.swevo.2020.100675.

[70] Y. Tian, X. T. Zheng, X. Y. Zhang, Y. C. Jin. Efficient large-scale multiobjective optimization based on a competitive swarm optimizer. *IEEE Transactions on Cybernetics*, vol. 50, no. 8, pp. 3696–3708, 2020. DOI: 10.1109/TCYB.2019.2906383.

[71] X. Y. Wang, B. R. Zhang, J. Wang, K. Zhang, Y. C. Jin. A cluster-based competitive particle swarm optimizer with a sparse truncation operator for multi-objective optimization. *Swarm and Evolutionary Computation*, vol. 71, Article number 101083, 2022. DOI: 10.1016/j.swevo.2022.101083.

[72] H. Jiang, Z. G. Deng, M. L. Xu, X. J. He, T. L. Mao, Z. Q. Wang. An emotion evolution based model for collective behavior simulation. In *Proceedings of ACM SIGGRAPH Symposium on Interactive 3D Graphics and Games*, Montreal, Canada, Article number 10, 2018. DOI: 10.1145/3190834.3190844.

[73] M. L. Xu, C. C. Li, P. Lv, W. Chen, D. Manocha, Z. G. Deng, B. Zhou. Crowd simulation model integrating "physiology-psychology-physics" factors, [Online], Available: https://arxiv.org/pdf/1801.00216v1.pdf, 2017.

[74] X. Hong, G. J. Zhang, D. J. Lu, H. Liu, L. Zhu, M. L. Xu. Personalized crowd emotional contagion coupling the virtual and physical cyberspace. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 52, no. 3, pp. 1638–1652, 2022. DOI: 10.1109/TSMC.2020.3034395.

[75] M. L. Xu, C. C. Li, P. Lv, W. Chen, Z. G. Deng, B. Zhou, D. Manocha. Emotion-based crowd simulation model based on physical strength consumption for emergency scenarios. *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 11, pp. 6977–6991, 2021. DOI: 10.1109/TITS.2020.3000607.

[76] M. L. Xu, X. Z. Xie, P. Lv, J. W. Niu, H. Wang, C. C. Li, R. J. Zhu, Z. G. Deng, B. Zhou. Crowd behavior simulation with emotional contagion in unexpected multihazard situations. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 51, no. 3, pp. 1567–1581, 2019. DOI: 10.1109/TSMC.2019.2899047.

[77] J. H. Wang, S. M. Lo, J. H. Sun, Q. S. Wang, H. L. Mu. Qualitative simulation of the panic spread in large-scale evacuation. *Simulation*, vol. 88, no. 12, pp. 1465–1474, 2012. DOI: 10.1177/0037549712456884.

[78] N. R. Johnson. Panic at "The who concert stampede": An empirical assessment. *Social Problems*, vol. 34, no. 4, pp. 362–373, 1987. DOI: 10.2307/800813.

[79] G. J. Zhang, D. J. Lu, H. Liu. Strategies to utilize the positive emotional contagion optimally in crowd evacuation. *IEEE Transactions on Affective Computing*, vol. 11, no. 4, pp. 708–721, 2020. DOI: 10.1109/TAFFC.2018.2836462.

[80] Y. Mao, S. W. Yang, Z. N. Li, Y. J. Li. Personality trait and group emotion contagion based crowd simulation for emergency evacuation. *Multimedia Tools and Applications*, vol. 79, no. 5, pp. 3077–3104, 2020. DOI: 10.1007/s11042-018-6069-3.

[81] J. X. Xue, H. Yin, P. Lv, M. L. Xu, Y. F. Li. Crowd queuing simulation with an improved emotional contagion model. *Science China Information Sciences*, vol. 62, no. 4, Article number 44101, 2019. DOI: 10.1007/s11432-018-9654-6.

[82] P. Lv, Z. J. Zhang, C. C. Li, Y. B. Guo, B. Zhou, M. L. Xu. Crowd behavior evolution with emotional contagion in political rallies. *IEEE Transactions on Computational Social Systems*, vol. 6, no. 2, pp. 377–386, 2019. DOI: 10.1109/TCSS.2018.2878461.

[83] C. C. Li, P. Lv, D. Manocha, H. Wang, Y. F. Li, B. Zhou, M. L. Xu. ACSEE: Antagonistic crowd simulation model with emotional contagion and evolutionary game theory. *IEEE Transactions on Affective Computing*, vol. 13, no. 2, pp. 729–745, 2022. DOI: 10.1109/TAFFC.2019.2954394.

[84] S. Doctor, G. K. Venayagamoorthy, V. G. Gudise. Optimal PSO for collective robotic search applications. In *Proceedings of Congress on Evolutionary Computation*, IEEE, Portland, USA, pp. 1390-1395, 2004. DOI: 10.1109/CEC.2004.1331059.

[85] J. H. Liang, C. H. Lee. Efficient collision-free path-planning of multiple mobile robots system using efficient artificial bee colony algorithm. *Advances in Engineering Software*, vol. 79, pp. 47–56, 2015. DOI: 10.1016/j.advengsoft.2014.09.006.

[86] G. G. Wang, H. E. Chu, S. Mirjalili. Three-dimensional path planning for UCAV using an improved bat algorithm. *Aerospace Science and Technology*, vol. 49, pp. 231–238, 2016. DOI: 10.1016/j.ast.2015.11.040.

[87] C. Z. Qu, W. D. Gai, M. Y. Zhong, J. Zhang. A novel reinforcement learning based grey wolf optimizer algorithm for unmanned aerial vehicles (UAVs) path planning. *Applied Soft Computing*, vol. 89, Article number 106099, 2020. DOI: 10.1016/j.asoc.2020.106099.

[88] P. Pandey, A. Shukla, R. Tiwari. Three-dimensional path planning for unmanned aerial vehicles using glowworm swarm optimization algorithm. *International Journal of System Assurance Engineering and Management*, vol. 9, no. 4, pp. 836–852, 2018. DOI: 10.1007/s13198-017-0663-z.

[89] P. K. Das, H. S. Behera, B. K. Panigrahi. A hybridization of an improved particle swarm optimization and gravitational search algorithm for multi-robot path planning. *Swarm and Evolutionary Computation*, vol. 28, pp. 14–28, 2016. DOI: 10.1016/j.swevo.2015.10.011.

[90] C. Z. Qu, W. D. Gai, J. Zhang, M. Y. Zhong. A novel hybrid grey wolf optimizer algorithm for unmanned aerial vehicle (UAV) path planning. *Knowledge-Based Systems*, vol. 194, Article number 105530, 2020. DOI: 10.1016/j.knosys.2020.105530.

[91] W. J. He, X. G. Qi, L. F. Liu. A novel hybrid particle swarm optimization for multi-UAV cooperate path planning. *Applied Intelligence*, vol. 51, no. 10, pp. 7350–7364, 2021. DOI: 10.1007/s10489-020-02082-8.

[92] H. Wang, X. Y. He, L. Y. Chen, J. R. Yin, L. Han, H. Liang, F. B. Zhu, R. J. Zhu, Z. M. Gao, M. L. Xu. Cognition-driven traffic simulation for unstructured road networks. *Journal of Computer Science and Technology*, vol. 35, no. 4, pp. 875–888, 2020. DOI: 10.1007/s11390-020-9598-y.

[93] H. Wang, M. L. Xu, F. B. Zhu, Z. G. Deng, Y. F. Li, B. Zhou. Shadow traffic: A unified model for abnormal traffic behavior simulation. *Computers & Graphics*, vol. 70, pp. 235–241, 2018. DOI: 10.1016/j.cag.2017.07.004.

[94] M. Land, J. Horwood. Which parts of the road guide steering? *Nature*, vol. 377, no. 6547, pp. 339–340, 1995. DOI: 10.1038/377339a0.

[95] X. Y. Wang, J. Q. Wang, J. L. Zhang, X. J. Ban. Lane-changing model with dynamic consideration of driver's propensity. *International Journal of Modern Physics C*, vol. 26, no. 2, Article number 1550015, 2015. DOI: 10.1142/S0129183115500151.

[96] M. L. Xu, H. Wang, S. L. Chu, Y. Gan, X. H. Jiang, Y. F. Li, B. Zhou. Traffic simulation and visual verification in smog. *ACM Transactions on Intelligent Systems and Technology*, vol. 10, no. 1, Article number 3, 2019. DOI: 10.1145/3200491.

[97] C. Pêcher, C. Lemercier, J. M. Cellier. Emotions drive attention: Effects on driver's behaviour. *Safety Science*, vol. 47, no. 9, pp. 1254–1259, 2009. DOI: 10.1016/j.ssci.2009.03.011.

[98] O. Taubman-Ben-Ari. The effects of positive emotion priming on self-reported reckless driving. *Accident Analysis & Prevention*, vol. 45, pp. 718–725, 2012. DOI: 10.1016/j.aap.2011.09.039.

[99] J. Y. Lu, X. F. Xie, R. G. Zhang. Focusing on appraisals: How and why anger and fear influence driving risk perception. *Journal of Safety Research*, vol. 45, pp. 65–73, 2013. DOI: 10.1016/j.jsr.2013.01.009.

[100] X. E. Zhang. China in global landscape of life sciences. *Bulletin of Chinese Academy of Sciences*, vol. 37, no. 5, pp. 622–635, 2022. DOI: 10.16418/j.issn.1000-3045.20220426003. (in Chinese)

[101] S. W. Li, O. Zeliger, L. Strahs, R. Báez-Mendoza, L. M. Johnson, A. M. Wojciechowski, Z. M. Williams. Frontal neurons driving competitive behaviour and ecology of social groups. *Nature*, vol. 603, no. 7902, pp. 661–666, 2022. DOI: 10.1038/s41586-021-04000-5.

[102] N. Padilla-Coreano, K. Batra, M. Patarino, Z. X. Chen, R. R. Rock, R. H. Zhang, S. B. Hausmann, J. C. Weddington, R. Patel, Y. E. Zhang, H. S. Fang, S. Mishra, D. O. LeDuke, J. Revanna, H. Li, M. Borio, R. Pamintuan, A. Bal, L. R. Keyes, A. Libster, R. Wichmann, F. Mills, F. H. Taschbach, G. A. Matthews, J. P. Curley, I. R. Fiete, C. W. Lu, K. M. Tye. Cortical ensembles orchestrate social competition through hypothalamic outputs. *Nature*, vol. 603, no. 7902, pp. 667–671, 2022. DOI: 10.1038/s41586-022-04507-5.

[103] C. Lyu, L. F. Abbott, G. Maimon. Building an allocentric travelling direction signal via vector computation. *Nature*, vol. 601, no. 7891, pp. 92–97, 2022. DOI: 10.1038/s41586-021-04067-0.

[104] G. L. Bon. *The Crowd: A Study of the Popular Mind*, London, UK: Fischer, 1896.

[105] D. Helbing, P. Molnár. Social force model for pedestrian dynamics. *Physical Review E*, vol. 51, no. 5, pp. 4282–4286, 1995. DOI: 10.1103/PhysRevE.51.4282.

[106] R. L. Hughes. A continuum theory for the flow of pedestrians. *Transportation Research Part B: Methodological*, vol. 36, no. 6, pp. 507–535, 2002. DOI: 10.1016/S0191-2615(01)00015-7.

[107] R. L. Hughes. The flow of human crowds. *Annual Review of Fluid Mechanics*, vol. 35, no. 1, pp. 169–182, 2003. DOI: 10.1146/annurev.fluid.35.101101.161136.

[108] B. G. Silverman, M. Johns, J. Cornwell, K. O'Brien. Human behavior models for agents in simulators and games: Part I: Enabling science with PMFserv. *Presence: Teleoperators and Virtual Environments*, vol. 15, no. 2, pp. 139–162, 2006. DOI: 10.1162/pres.2006.15.2.139.

[109] N. Bain, D. Bartolo. Dynamic response and hydrodynamics of polarized crowds. *Science*, vol. 363, no. 6422, pp. 46–49, 2019. DOI: 10.1126/science.aat9891.

[110] A. Treuille, S. Cooper, Z. Popoviá. Continuum crowds. *ACM Transactions on Graphics*, vol. 25, no. 3, pp. 1160–1168, 2006. DOI: 10.1145/1141911.1142008.

[111] H. Jiang, W. B. Xu, T. L. Mao, C. P. Li, S. H. Xia, Z. Q. Wang. Continuum crowd simulation in complex environments. *Computers & Graphics*, vol. 34, no. 5, pp. 537–544, 2010. DOI: 10.1016/j.cag.2010.05.013.

[112] Q. W. Chao, P. F. Liu, Y. Han, Y. Y. Lin, C. N. Li, Q. G. Miao, X. G. Jin. A calibrated force-based model for mixed traffic simulation. *IEEE Transactions on Visualization and Computer Graphics*, to be published. DOI: 10.1109/TVCG.2021.3128286.

[113] L. C. Jiao, L. Wang. A novel genetic algorithm based on immunity. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, vol. 30, no. 5, pp. 552–561, 2000. DOI: 10.1109/3468.867862.

[114] G. Dhiman, M. Garg, A. Nagar, V. Kumar, M. Dehghani. A novel algorithm for global optimization: Rat swarm optimizer. *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, no. 8, pp. 8457–8482, 2021. DOI: 10.1007/s12652-020-02580-0.

[115] T. S. Shen. ESM: A building evacuation simulation model. *Building and Environment*, vol. 40, no. 5, pp. 671–680, 2005. DOI: 10.1016/j.buildenv.2004.08.029.

[116] J. Tian. The physics and simulation of occupant traffic flow in the case of evacuating public building area. *Transportation Research Part D: Transport and Environment*, vol. 30, pp. 76–85, 2014. DOI: 10.1016/j.trd.2014.05.009.

[117] N. Wagner, V. Agrawal. An agent-based simulation system for concert venue crowd evacuation modeling in the presence of a fire disaster. *Expert Systems with Applications*, vol. 41, no. 6, pp. 2807–2815, 2014. DOI: 10.1016/j.eswa.2013.10.013.

[118] R. S. C. Lee, R. L. Hughes. Exploring trampling and crushing in a crowd. *Journal of Transportation Engineering*, vol. 131, no. 8, pp. 575–582, 2005. DOI: 10.1061/(ASCE)0733-947X(2005)131:8(575).

[119] R. S. C. Lee, R. L. Hughes. Minimisation of the risk of trampling in a crowd. *Mathematics and Computers in Simulation*, vol. 74, no. 1, pp. 29–37, 2007. DOI: 10.1016/j.matcom.2006.06.029.

[120] J. Ma, S. M. Lo, W. G. Song, W. L. Wang, J. Zhang, G. X. Liao. Modeling pedestrian space in complex building for efficient pedestrian traffic simulation. *Automation in Construction*, vol. 30, pp. 25–36, 2013. DOI: 10.1016/j.autcon.2012.11.032.

[121] K. Castañeda, O. Sánchez, R. F. Herrera, E. Pellicer, H. Porras. BIM-based traffic analysis and simulation at road intersection design. *Automation in Construction*, vol. 131, Article number 103911, 2021. DOI: 10.1016/j.autcon.2021.103911.

[122] S. P. Zhou, D. Chen, W. T. Cai, L. B. Luo, M. Y. H. Low, F. Tian, V. S. H. Tay, D. W. S. Ong. Crowd modeling and simulation technologies. *ACM Transactions on Modeling and Computer Simulation*, vol. 20, no. 4, Article number 20, 2010. DOI: 10.1145/1842722.1842725.

[123] Y. Yuan, Z. K. Wu, M. Q. Zhou. Populating virtual environments with crowd patches and rule-based method. In *Proceedings of the 11th ACM SIGGRAPH International Conference on Virtual-reality Continuum and its Applications in Industry*, Singapore, pp. 239-246, 2012. DOI: 10.1145/2407516.2407574.

[124] Q. W. Chao, Z. G. Deng, X. G. Jin. Vehicle-pedestrian interaction for mixed traffic simulation. *Computer Animation and Virtual Worlds*, vol. 26, no. 3–4, pp. 405–412, 2015. DOI: 10.1002/cav.1654.

[125] T. Toffoli, N. Margolus. *Cellular Automata Machines: A New Environment for Modeling*. Cambridge, USA: MIT Press, 1987.

[126] K. Nagel, M. Schreckenberg. A cellular automaton model for freeway traffic. *Journal de Physique*, vol. 2, no. 12, pp. 2221–2229, 1992. DOI: 10.1051/jp1:1992277.

[127] K. Nagel, C. L. Barrett, M. Rickert. Parallel Traffic Micro-simulation by Cellular Automata and Application for Large Scale Transportation Modeling. Technical Report, Federal Highway Administration, Department of Transportation, USA, [Online], Available: https://rosap.ntl.bts.gov/view/dot/57245, 1996.

[128] M. Rickert, K. Nagel, M. Schreckenberg, A. Latour. Two lane traffic simulations using cellular automata. *Physica A: Statistical Mechanics and its Applications*, vol. 231, no. 4, pp. 534–550, 1996. DOI: 10.1016/0378-4371(95)00442-4.

[129] V. J. Blue, J. L. Adler. Emergent fundamental pedestrian flows from cellular automata microsimulation. *Transportation Research Record*, vol. 1644, no. 1, pp. 29–36, 1998. DOI: 10.3141/1644-04.

[130] V. J. Blue, J. L. Adler. Cellular automata microsimulation for modeling bi-directional pedestrian walkways. *Transportation Research Part B: Methodological*, vol. 35, no. 3, pp. 293–312, 2001. DOI: 10.1016/s0191-2615(99)00052-1.

[131] C. Burstedde, K. Klauck, A. Schadschneider, J. Zittartz. Simulation of pedestrian dynamics using a two-dimensional cellular automaton. *Physica A: Statistical Mechanics and Its Applications*, vol. 295, no. 3–4, pp. 507–525, 2001. DOI: 10.1016/S0378-4371(01)00141-8.

[132] R. F. Zhao, Y. Zhai, L. Qu, R. H. Wang, Y. Y. Huang, Q. Dong. A continuous floor field cellular automata model with interaction area for crowd evacuation. *Physica A: Statistical Mechanics and Its Applications*, vol. 575, Article number 126049, 2021. DOI: 10.1016/j.physa.2021.126049.

[133] L. L. Lu, C. Y. Chan, J. Wang, W. Wang. A study of pedestrian group behaviors in crowd evacuation based on an extended floor field cellular automaton model. *Transportation Research Part C: Emerging Technologies*, vol. 81, pp. 317–329, 2017. DOI: 10.1016/j.trc.2016.08.018.

[134] A. Kirchner, A. Schadschneider. Simulation of evacuation processes using a bionics-inspired cellular automaton model for pedestrian dynamics. *Physica A: Statistical Mechanics and Its Applications*, vol. 312, no. 1–2, pp. 260–276, 2002. DOI: 10.1016/s0378-4371(02)00857-9.

[135] M. Muramatsu, T. Irie, T. Nagatani. Jamming transition in pedestrian counter flow. *Physica A: Statistical Mechanics and Its Applications*, vol. 267, no. 3–4, pp. 487–498, 1999. DOI: 10.1016/S0378-4371(99)00018-7.

[136] M. Muramatsu, T. Nagatani. Jamming transition in two-dimensional pedestrian traffic. *Physica A: Statistical Mechanics and its Applications*, vol. 275, no. 1–2, pp. 281–291, 2000. DOI: 10.1016/S0378-4371(99)00447-1.

[137] X. Ruan, J. Y. Zhou, H. Z. Tu, Z. R. Jin, X. F. Shi. An improved cellular automaton with axis information for microscopic traffic simulation. *Transportation Research Part C*: *Emerging Technologies*, vol. 78, pp. 63–77, 2017. DOI: 10.1016/j.trc.2017.02.023.

[138] M. Y. Liu, J. Shi. A cellular automata traffic flow model combined with a BP neural network based microscopic lane changing decision model. *Journal of Intelligent Transportation Systems*, vol. 23, no. 4, pp. 309–318, 2019. DOI: 10.1080/15472450.2018.1462176.

[139] J. H. Wang, W. Lv, Y. J. Jiang, S. S. Qin, J. W. Li. A multi-agent based cellular automata model for intersection traffic control simulation. *Physica A*: *Statistical Mechanics and Its Applications*, vol. 584, Article number 126356, 2021. DOI: 10.1016/j.physa.2021.126356.

[140] A. Kirchner, H. Klüpfel, K. Nishinari, A. Schadschneider, M. Schreckenberg. Simulation of competitive egress behavior: Comparison with aircraft evacuation data. *Physica A*: *Statistical Mechanics and its Applications*, vol. 324, no. 3–4, pp. 689–697, 2003. DOI: 10.1016/S0378-4371(03)00076-1.

[141] W. G. Weng, T. Chen, H. Y. Yuan, W. C. Fan. Cellular automaton simulation of pedestrian counter flow with different walk velocities. *Physical Review E*, vol. 74, no. 3, Article number 036102, 2006. DOI: 10.1103/PhysRevE.74.036102.

[142] K. Yamamoto, S. Kokubo, K. Nishinari. Simulation for pedestrian dynamics by real-coded cellular automata (RCA). *Physica A*: *Statistical Mechanics and its Applications*, vol. 379, no. 2, pp. 654–660, 2007. DOI: 10.1016/j.physa.2007.02.040.

[143] Y. W. Fu, J. H. Liang, Q. P. Liu, X. Q. Hu. Crowd simulation for evacuation behaviors based on multi-agent system and cellular automaton. In *Proceedings of International Conference on Virtual Reality and Visualization*, IEEE, Shenyang, China, pp. 103–109, 2014. DOI: 10.1109/ICVRV.2014.52.

[144] T. I. Lakoba, D. J. Kaup, N. M. Finkelstein. Modifications of the helbing-molnar-farkas-vicsek social force model for pedestrian evolution. *Simulation*, vol. 81, no. 5, pp. 339–352, 2005. DOI: 10.1177/0037549705052772.

[145] W. J. Yu, R. Chen, L. Y. Dong, S. Q. Dai. Centrifugal force model for pedestrian dynamics. *Physical Review E*, vol. 72, no. 2, Article number 026112, 2005. DOI: 10.1103/PhysRevE.72.026112.

[146] M. Chraibi, U. Kemloh, A. Schadschneider, A. Seyfried. Force-based models of pedestrian dynamics. *Networks and Heterogeneous Media*, vol. 6, no. 3, pp. 425–442, 2011. DOI: 10.3934/nhm.2011.6.425.

[147] M. Chraibi, A. Seyfried, A. Schadschneider. Generalized centrifugal-force model for pedestrian dynamics. *Physical Review E*, vol. 82, no. 4, Article number 046111, 2010. DOI: 10.1103/PhysRevE.82.046111.

[148] F. Pascucci, N. Rinke, C. Schiermeyer, B. Friedrich, V. Berkhahn. Modeling of shared space with multi-modal traffic using a multi-layer social force approach. *Transportation Research Procedia*, vol. 10, pp. 316–326, 2015. DOI: 10.1016/j.trpro.2015.09.081.

[149] L. Huang, J. P. Wu, F. You, Z. H. Lv, H. B. Song. Cyclist social force model at unsignalized intersections with heterogeneous traffic. *IEEE Transactions on Industrial Informatics*, vol. 13, no. 2, pp. 782–792, 2017. DOI: 10.1109/TII.2016.2597744.

[150] Y. Q. Jiang, B. K. Chen, X. Li, Z. J. Ding. Dynamic navigation field in the social force model for pedestrian evacuation. *Applied Mathematical Modelling*, vol. 80, pp. 815–826, 2020. DOI: 10.1016/j.apm.2019.10.016.

[151] N. Pelechano, J. M. Allbeck, N. I. Badler. Controlling individual agents in high-density crowd simulation. In *Proceedings of ACM SIGGRAPH/Eurographics Symposium on Computer Animation*, San Diego, USA, pp. 99–108, 2007.

[152] W. H. Wu, M. Y. Chen, J. H. Li, B. L. Liu, X. P. Zheng. An extended social force model via pedestrian heterogeneity affecting the self-driven force. *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 7, pp. 7974–7986, 2022. DOI: 10.1109/TITS.2021.3074914.

[153] M. R. C. McDowell. Kinetic theory of vehicular traffic. *Journal of the Operational Research Society*, vol. 23, no. 4, pp. 599–600, 1972. DOI: 10.1057/jors.1972.98.

[154] D. Helbing. A fluid dynamic model for the movement of pedestrians, [Online], Available: https://arxiv.org/abs/cond-mat/9805213, 1998.

[155] M. J. Lighthill, G. B. Whitham. On kinematic waves II. A theory of traffic flow on long crowded roads. *Proceedings of the Royal Society A*: *Mathematical, Physical and Engineering Sciences*, vol. 229, no. 1178, pp. 317–345, 1955. DOI: 10.1098/rspa.1955.0089.

[156] S. Chenney. Flow tiles. In *Proceedings of ACM SIGGRAPH/Eurographics symposium on Computer animation*, Grenoble, France, pp. 233–242, 2004. DOI: 10.1145/1028523.1028553.

[157] V. Coscia, C. Canavesio. First-order macroscopic modelling of human crowd dynamics. *Mathematical Models and Methods in Applied Sciences*, vol. 18, no. S1, pp. 1217–1247, 2008. DOI: 10.1142/S0218202508003017.

[158] R. Narain, A. Golas, S. Curtis, M. C. Lin. Aggregate dynamics for dense crowd simulation. In *Proceedings of ACM SIGGRAPH Asia*, Yokohama, Japan, Article number 122, 2009. DOI: 10.1145/1661412.1618468.

[159] N. Bellomo, S. Berrone, L. Gibelli, A. Pieri. First order models of human crowds with behavioral-social dynamics, [Online], Available: https://doi.org/10.48550/arXiv.1501.02828, 2015.

[160] R. Mohan, G. Ramadurai. Heterogeneous traffic flow modelling using second-order macroscopic continuum model. *Physics Letters A*, vol. 381, no. 3, pp. 115–123, 2017. DOI: 10.1016/j.physleta.2016.10.042.

[161] H. Y. Liang, J. Du, S. C. Wong. A Continuum model for pedestrian flow with explicit consideration of crowd force and panic effects. *Transportation Research Part B*: *Methodological*, vol. 149, pp. 100–117, 2021. DOI: 10.1016/j.trb.2021.05.006.

[162] O. Khatib. Real-time obstacle avoidance for manipulators and mobile robots. *The International Journal of Robotics Research*, vol. 5, no. 1, pp. 90–98, 1986. DOI: 10.1177/027836498600500106.

[163] Y. Q. Chen, T. X. Li. Collision avoidance of unmanned ships based on artificial potential field. In *Proceedings of Chinese Automation Congress*, IEEE, Jinan, China, pp. 4437–4440, 2017. DOI: 10.1109/CAC.2017.8243561.

[164] H. I. Lin, M. F. Hsieh. Robotic arm path planning based on three-dimensional artificial potential field. In *Proceedings of the 18th International Conference on Control, Automation and Systems*, IEEE, PyeongChang, Repub-

lic of Korea, pp. 740–745, 2018.

[165] J. Song, C. Hao, J. C. Su. Path planning for unmanned surface vehicle based on predictive artificial potential field. *International Journal of Advanced Robotic Systems*, vol. 17, no. 2, pp. 1–13, 2020. DOI: 10.1177/1729881420918461.

[166] Z. Y. Chen, L. Ma, Z. J. Shao. Path planning for obstacle avoidance of manipulators based on improved artificial potential field. In *Proceedings of Chinese Automation Congress*, IEEE, Hangzhou, China, pp. 2991–2996, 2019. DOI: 10.1109/CAC48633.2019.8996467.

[167] Y. B. Zheng, B. Li, D. Y. An, N. Li. A multi-agent path planning algorithm based on hierarchical reinforcement learning and artificial potential field. In *Proceedings of the 11th International Conference on Natural Computation*, IEEE, Zhangjiajie, China, pp. 363–369, 2015. DOI: 10.1109/ICNC.2015.7378017.

[168] Y. Noguchi, T. Maki. Path planning method based on artificial potential field and reinforcement learning for intervention AUVs. In *Proceedings of IEEE Underwater Technology*, Kaohsiung, China, 2019. DOI: 10.1109/UT.2019.8734314.

[169] H. X. Li, D. X. Gong, J. J. Yu. An obstacles avoidance method for serial manipulator based on reinforcement learning and artificial potential field. *International Journal of Intelligent Robotics and Applications*, vol. 5, no. 2, pp. 186–202, 2021. DOI: 10.1007/s41315-021-00172-5.

[170] H. Wang, Y. F. He, Z. Wang, G. F. Li, Y. Q. Xiao, M. L. Xu. Data-driven online traffic reconstructions: Interactively optimizing in virtual reality. *Computers & Graphics*, vol. 105, pp. 85–93, 2022. DOI: 10.1016/j.cag.2022.03.012.

[171] A. Lerner, Y. Chrysanthou, D. Lischinski. Crowds by example. *Computer Graphics Forum*, vol. 26, no. 3, pp. 655–664, 2007. DOI: 10.1111/j.1467-8659.2007.01089.x.

[172] K. H. Lee, M. G. Choi, Q. Hong, J. Lee. Group behavior from video: A data-driven approach to crowd simulation. In *Proceedings of ACM SIGGRAPH/Eurographics Symposium on Computer Animation*, San Diego, USA, pp. 109–118, 2007.

[173] A. Lerner, E. Fitusi, Y. Chrysanthou, D. Cohen-Or. Fitting behaviors to pedestrian simulations. In *Proceedings of ACM SIGGRAPH/Eurographics Symposium on Computer Animation*, New Orleans, USA, pp. 199–208, 2009. DOI: 10.1145/1599470.1599496.

[174] X. Wang, R. Jiang, L. Li, Y. L. Lin, X. H. Zheng, F. Y. Wang. Capturing car-following behaviors by deep learning. *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 3, pp. 910–920, 2018. DOI: 10.1109/TITS.2017.2706963.

[175] H. K. Bi, T. L. Mao, Z. Q. Wang, Z. G. Deng. A deep learning-based framework for intersectional traffic simulation and editing. *IEEE Transactions on Visualization and Computer Graphics*, vol. 26, no. 7, pp. 2335–2348, 2020. DOI: 10.1109/TVCG.2018.2889834.

[176] X. Wei, W. Lu, L. L. Zhu, W. W. Xing. Learning motion rules from real data: Neural network for crowd simulation. *Neurocomputing*, vol. 310, pp. 125–134, 2018. DOI: 10.1016/j.neucom.2018.05.022.

[177] Z. Z. Yao, G. J. Zhang, D. J. Lu, H. Liu. Learning crowd behavior from real data: A residual network method for crowd simulation. *Neurocomputing*, vol. 404, pp. 173–185, 2020. DOI: 10.1016/j.neucom.2020.04.141.

[178] X. D. Zhao, L. Xia, J. Zhang, W. G. Song. Artificial neural network based modeling on unidirectional and bidirectional pedestrian flow at straight corridors. *Physica A: Statistical Mechanics and Its Applications*, vol. 547, Article number 123825, 2020. DOI: 10.1016/j.physa.2019.123825.

[179] D. F. Xie, Z. Z. Fang, B. Jia, Z. B. He. A data-driven lane-changing model based on deep learning. *Transportation Research Part C: Emerging Technologies*, vol. 106, pp. 41–60, 2019. DOI: 10.1016/j.trc.2019.07.002.

[180] H. K. Bi, T. L. Mao, Z. Q. Wang, Z. G. Deng. A data-driven model for lane-changing in traffic simulation. In *Proceedings of the ACM SIGGRAPH/Eurographics Symposium on Computer Animation*, Zurich, Switzerland, pp. 149–158, 2016.

[181] X. Song, K. Chen, X. Li, J. H. Sun, B. C. Hou, Y. Cui, B. C. Zhang, G. Xiong, Z. L. Wang. Pedestrian trajectory prediction based on deep convolutional LSTM network. *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 6, pp. 3285–3302, 2021. DOI: 10.1109/TITS.2020.2981118.

[182] X. D. Zhao, J. Zhang, W. G. Song. A Radar-Nearest-Neighbor based data-driven approach for crowd simulation. *Transportation Research Part C: Emerging Technologies*, vol. 129, Article number 103260, 2021. DOI: 10.1016/j.trc.2021.103260.

[183] X. Song, D. L. Han, J. H. Sun, Z. H. Zhang. A data-driven neural network approach to simulate pedestrian movement. *Physica A: Statistical Mechanics and its Applications*, vol. 509, pp. 827–844, 2018. DOI: 10.1016/j.physa.2018.06.045.

[184] K. Tkachuk, X. Song, I. Maltseva. Application of artificial neural networks for agent-based simulation of emergency evacuation from buildings for various purpose. *IOP Conference Series: Materials Science and Engineering*, vol. 365, no. 4, Article number 042064, 2018. DOI: 10.1088/1757-899X/365/4/042064.

[185] N. Courty, T. Corpetti. Crowd motion capture. *Computer Animation and Virtual Worlds*, vol. 18, no. 4–5, pp. 361–370, 2007. DOI: 10.1002/cav.199.

[186] S. R. Musse, C. R. Jung, J. C. Jr. Jacques, A. Braun. Using computer vision to simulate the motion of virtual agents. *Computer Animation and Virtual Worlds*, vol. 18, no. 2, pp. 83–93, 2007. DOI: 10.1002/cav.163.

[187] J. H. Zhong, W. T. Cai, L. B. Luo, H. Y. Yin. Learning behavior patterns from video: A data-driven framework for agent-based crowd modeling. In *Proceedings of the International Conference on Autonomous Agents and Multiagent Systems*, Istanbul, Turkey, pp. 801–809, 2015.

[188] J. H. Zhong, W. T. Cai, M. Lees, L. B. Luo. Automatic model construction for the behavior of human crowds. *Applied Soft Computing*, vol. 56, pp. 368–378, 2017. DOI: 10.1016/j.asoc.2017.03.020.

[189] S. Patil, J. Van Den Berg, S. Curtis, M. C. Lin, D. Manocha. Directing crowd simulations using navigation fields. *IEEE Transactions on Visualization and Computer Graphics*, vol. 17, no. 2, pp. 244–254, 2011. DOI: 10.1109/TVCG.2010.33.

[190] M. Hu, S. Ali, M. Shah. Learning motion patterns in crowded scenes using motion flow field. In *Proceedings of the 19th International Conference on Pattern Recogni-*

tion, IEEE, Tampa, USA, 2008. DOI: 10.1109/ICPR.2008.4761183.

[191] X. G. Jin, J. Y. Xu, C. C. L. Wang, S. S. Huang, J. Zhang. Interactive control of large-crowd navigation in virtual environments using vector fields. *IEEE Computer Graphics and Applications*, vol. 28, no. 6, pp. 37–46, 2008. DOI: 10.1109/MCG.2008.117.

[192] S. Wu, H. Yang, S. B. Zheng, H. Su, Y. W. Fan, M. H. Yang. Crowd behavior analysis via curl and divergence of motion trajectories. *International Journal of Computer Vision*, vol. 123, no. 3, pp. 499–519, 2017. DOI: 10.1007/s11263-017-1005-y.

[193] N. Nayan, S. S. Sahu, S. Kumar. Detecting anomalous crowd behavior using correlation analysis of optical flow. *Signal, Image and Video Processing*, vol. 13, no. 6, pp. 1233–1241, 2019. DOI: 10.1007/s11760-019-01474-9.

[194] S. D. Khan. Congestion detection in pedestrian crowds using oscillation in motion trajectories. *Engineering Applications of Artificial Intelligence*, vol. 85, pp. 429–443, 2019. DOI: 10.1016/j.engappai.2019.07.009.

[195] D. H. Lin, E. Grimson, J. Fisher. Learning visual flows: A Lie algebraic approach. In *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition*, Miami, USA, pp. 747–754, 2009. DOI: 10.1109/CVPR.2009.5206660.

[196] D. H. Lin, E. Grimson, J. Fisher. Modeling and estimating persistent motion with geometric flows. In *Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, San Francisco, USA, pp. 1783–1790, 2010. DOI: 10.1109/CVPR.2010.5539848.

[197] Y. W. Fan, H. Yang, S. B. Zheng, H. Su. Geometric motion flow (GMF): A new feature for traffic surveillance. In *Proceedings of the 6th International Conference on Image and Graphics*, IEEE, Hefei, China, pp. 726–730, 2011. DOI: 10.1109/ICIG.2011.56.

[198] C. Rudloff, D. Bauer, T. Matyus, S. Seer. Mind the gap: Boarding and alighting processes using the social force paradigm calibrated on experimental data. In *Proceedings of the 14th International IEEE Conference on Intelligent Transportation Systems*, Washington DC, USA, pp. 353–358, 2011. DOI: 10.1109/ITSC.2011.6083077.

[199] S. Seer, N. Brändle, C. Ratti. Kinects and human kinetics: A new approach for studying crowd behavior, [Online], Available: https://arxiv.org/abs/1210.2838, 2012.

[200] M. Tang, H. F. Jia. An approach for calibration and validation of the social force pedestrian model. In *Proceedings of International Conference on Transportation, Mechanical, and Electrical Engineering*, IEEE, Changchun, China, pp. 2026–2031, 2011. DOI: 10.1109/TMEE.2011.6199614.

[201] M. Ko, T. Kim, K. Sohn. Calibrating a social-force-based pedestrian walking model based on maximum likelihood estimation. *Transportation*, vol. 40, no. 1, pp. 91–107, 2013. DOI: 10.1007/s11116-012-9411-z.

[202] S. Seer, C. Rudloff, T. Matyus, N. Brändle. Validating social force based models with comprehensive real world motion data. *Transportation Research Procedia*, vol. 2, pp. 724–732, 2014. DOI: 10.1016/j.trpro.2014.09.080.

[203] M. X. Liu, W. L. Zeng, P. Chen, X. Y. Wu. A microscopic simulation model for pedestrian-pedestrian and pedestrian-vehicle interactions at crosswalks. *PLoS One*, vol. 12, no. 7, Article number e0180992, 2017. DOI: 10.1371/journal.pone.0180992.

[204] R. Lovreglio, C. Dias, X. Song, L. Ballerini. Towards microscopic calibration of pedestrian simulation models using open trajectory datasets: The case study of the edinburgh informatics forum. In *Proceedings of International Conference on Traffic and Granular Flow*, Springer, Washington DC, USA, pp. 215–223, 2017. DOI: 10.1007/978-3-030-11440-4_25.

[205] S. Lemercier, A. Jelic, R. Kulpa, J. Hua, J. Fehrenbach, P. Degond, C. Appert-Rolland, S. Donikian, J. Pettré. Realistic following behaviors for crowd simulation. *Computer Graphics Forum*, vol. 31, no. 2, pp. 489–498, 2012. DOI: 10.1111/j.1467-8659.2012.03028.x.

[206] B. Anvari, M. G. H. Bell, A. Sivakumar, W. Y. Ochieng. Modelling shared space users via rule-based social force model. *Transportation Research Part C: Emerging Technologies*, vol. 51, pp. 83–103, 2015. DOI: 10.1016/j.trc.2014.10.012.

[207] W. L. Zeng, P. Chen, G. Z. Yu, Y. P. Wang. Specification and calibration of a microscopic model for pedestrian dynamic simulation at signalized intersections: A hybrid approach. *Transportation Research Part C: Emerging Technologies*, vol. 80, pp. 37–70, 2017. DOI: 10.1016/j.trc.2017.04.009.

[208] M. Hussein, T. Sayed. Validation of an agent-based microscopic pedestrian simulation model in a crowded pedestrian walking environment. *Transportation Planning and Technology*, vol. 42, no. 1, pp. 1–22, 2019. DOI: 10.1080/03081060.2018.1541279.

[209] N. Bode. Parameter calibration in crowd simulation models using approximate Bayesian computation, [Online], Available: https://arxiv.org/abs/2001.10330, 2020.

[210] P. F. Liu, Q. W. Chao, H. W. Huang, Q. Y. Wang, Z. Y. Zhao, Q. Peng, M. K. Yip, E. S. Liu, X. G. Jin. Velocity-based dynamic crowd simulation by data-driven optimization. *The Visual Computer*, vol. 38, no. 9, pp. 3499–3512, 2022. DOI: 10.1007/s00371-022-02556-5.

[211] L. Torrey. Crowd simulation via multi-agent reinforcement learning. In *Proceedings of the 6th AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*, Stanford, USA, pp. 89–94, 2010.

[212] Y. Kato, K. Kamiyama, K. Morioka. Autonomous robot navigation system with learning based on deep Q-network and topological maps. In *Proceedings of IEEE/SICE International Symposium on System Integration*, IEEE, Taipei, China, pp. 1040–1046, 2017. DOI: 10.1109/SII.2017.8279360.

[213] S. M. Feng, H. L. Ren, X. R. Wang, P. Ben-Tzvi. Mobile robot obstacle avoidance based on deep reinforcement learning. In *Proceedings of ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, Anaheim, USA, 2019. DOI: 10.1115/DETC2019-97536.

[214] J. W. Zhang, J. T. Springenberg, J. Boedecker, W. Burgard. Deep reinforcement learning with successor features for navigation across similar environments. In *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems*, IEEE, Vancouver, Canada, pp. 2371–2378, 2017. DOI: 10.1109/IROS.2017.8206049.

[215] S. H. Hsu, S. H. Chan, P. T. Wu, K. Xiao, L. C. Fu. Distributed deep reinforcement learning based indoor visual navigation. In *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems*, IEEE,

Madrid, Spain, pp. 2532–2537, 2018. DOI: 10.1109/IROS.2018.8594352.

[216] C. Wang, J. Wang, X. D. Zhang, X. Zhang. Autonomous navigation of UAV in large-scale unknown complex environment with deep reinforcement learning. In *Proceedings of IEEE Global Conference on Signal and Information Processing*, Montreal, Canada, pp. 858–862, 2017. DOI: 10.1109/GlobalSIP.2017.8309082.

[217] C. Wang, J. Wang, Y. Shen, X. D. Zhang. Autonomous navigation of UAVs in large-scale complex environments: A deep reinforcement learning approach. *IEEE Transactions on Vehicular Technology*, vol. 68, no. 3, pp. 2124–2136, 2019. DOI: 10.1109/TVT.2018.2890773.

[218] C. Wang, J. Wang, J. J. Wang, X. D. Zhang. Deep-reinforcement-learning-based autonomous UAV navigation with sparse rewards. *IEEE Internet of Things Journal*, vol. 7, no. 7, pp. 6180–6190, 2020. DOI: 10.1109/JIOT.2020.2973193.

[219] D. Xu, X. Huang, Z. L. Li, X. Li. Local motion simulation using deep reinforcement learning. *Transactions in GIS*, vol. 24, no. 3, pp. 756–779, 2020. DOI: 10.1111/tgis.12620.

[220] D. Xu, X. Huang, J. Mango, X. Li, Z. L. Li. Simulating multi-exit evacuation using deep reinforcement learning. *Transactions in GIS*, vol. 25, no. 3, pp. 1542–1564, 2021. DOI: 10.1111/tgis.12738.

[221] R. J. Zhu, S. N. Wu, L. L. Li, P. Lv, M. L. Xu. Context-aware multiagent broad reinforcement learning for mixed pedestrian-vehicle adaptive traffic light control. *IEEE Internet of Things Journal*, vol. 9, no. 20, pp. 19694–19705, 2022. DOI: 10.1109/JIOT.2022.3167029.

[222] Z. Zhang, D. J. Lu, J. L. Y. Li, P. S. Liu, G. J. Zhang. Crowd evacuation simulation using hierarchical deep reinforcement learning. In *Proceedings of the 24th IEEE International Conference on Computer Supported Cooperative Work in Design*, Dalian, China, pp. 563–568, 2021. DOI: 10.1109/CSCWD49262.2021.9437632.

[223] D. Zhang, W. H. Li, J. H. Gong, L. Huang, G. Y. Zhang, S. Shen, J. T. Liu, H. N. Ma. HDRLM3D: A deep reinforcement learning-based model with human-like perceptron and policy for crowd evacuation in 3D environments. *ISPRS International Journal of Geo-information*, vol. 11, no. 4, Article number 255, 2022. DOI: 10.3390/ijgi11040255.

[224] A. D. Dragan, S. S. Srinivasa. A policy-blending formalism for shared control. *The International Journal of Robotics Research*, vol. 32, no. 7, pp. 790–805, 2013. DOI: 10.1177/0278364913490324.

[225] A. Broad, T. Murphey, B. Argall. Operation and imitation under safety-aware shared control. In *Proceedings of the 13th International Workshop on the Algorithmic Foundations of Robotics*, Springer, Mérida, Mexico, pp. 905–920, 2018. DOI: 10.1007/978-3-030-44051-0_52.

[226] R. C. Simpson, S. P. Levine. Automatic adaptation in the NavChair assistive wheelchair navigation system. *IEEE Transactions on Rehabilitation Engineering*, vol. 7, no. 4, pp. 452–463, 1999. DOI: 10.1109/86.808949.

[227] B. J. F. Driessen, T. K. T. Kate, F. Liefhebber, A. H. G. Versluis, J. A. Van Woerden. Collaborative control of the manus manipulator. *Universal Access in the Information Society*, vol. 4, no. 2, pp. 165–173, 2005. DOI: 10.1007/s10209-005-0121-6.

[228] Y. Xing, C. Lv, D. P. Cao, P. Hang. Toward human-vehicle collaboration: Review and perspectives on human-centered collaborative automated driving. *Transportation Research Part C: Emerging Technologies*, vol. 128, Article number 103199, 2021. DOI: 10.1016/j.trc.2021.103199.

[229] N. Jansen, M. Cubuktepe, U. Topcu. Synthesis of shared control protocols with provable safety and performance guarantees. In *Proceedings of American Control Conference*, IEEE, Seattle, USA, pp. 1866–1873, 2017. DOI: 10.23919/ACC.2017.7963224.

[230] D. Gopinath, S. Jain, B. D. Argall. Human-in-the-loop optimization of shared autonomy in assistive robotics. *IEEE Robotics and Automation Letters*, vol. 2, no. 1, pp. 247–254, 2017. DOI: 10.1109/LRA.2016.2593928.

[231] Y. Oh, S. W. Wu, M. Toussaint, J. Mainprice. Natural gradient shared control. In *Proceedings of the 29th IEEE International Conference on Robot and Human Interactive Communication*, Naples, Italy, pp. 1223–1229, 2020. DOI: 10.1109/RO-MAN47096.2020.9223465.

[232] W. X. Xu, J. Huang, Y. J. Wang, C. J. Tao, L. Cheng. Reinforcement learning-based shared control for walking-aid robot and its experimental verification. *Advanced Robotics*, vol. 29, no. 22, pp. 1463–1481, 2015. DOI: 10.1080/01691864.2015.1070748.

[233] S. Reddy, A. D. Dragan, S. Levine. Shared autonomy via deep reinforcement learning. In *Proceedings of the 14th Robotics: Science and Systems*, Pittsburgh, USA, 2018.

[234] C. B. Schaff, M. R. Walter. Residual policy learning for shared autonomy. In *Proceedings of the 14th Robotics: Science and Systems*, Corvalis, USA, 2020.

[235] Y. Oh, M. Toussaint, J. Mainprice. Learning to arbitrate human and robot control using disagreement between sub-policies. In *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems*, IEEE, Prague, Czech Republic, pp. 5305–5311, 2021. DOI: 10.1109/IROS51168.2021.9636049.

[236] K. Hauser. Recognition, prediction, and planning for assisted teleoperation of freeform tasks. *Autonomous Robots*, vol. 35, no. 4, pp. 241–254, 2013. DOI: 10.1007/s10514-013-9350-3.

[237] S. Javdani, H. Admoni, S. Pellegrinelli, S. S. Srinivasa, J. A. Bagnell. Shared autonomy via hindsight optimization for teleoperation and teaming. *The International Journal of Robotics Research*, vol. 37, no. 7, pp. 717–742, 2018. DOI: 10.1177/0278364918776060.

[238] S. Noh. Decision-making framework for autonomous driving at road intersections: Safeguarding against collision, overly conservative behavior, and violation vehicles. *IEEE Transactions on Industrial Electronics*, vol. 66, no. 4, pp. 3275–3286, 2019. DOI: 10.1109/TIE.2018.2840530.

[239] C. Xu, W. Z. Zhao, C. Y. Wang. An integrated threat assessment algorithm for decision-making of autonomous driving vehicles. *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 6, pp. 2510–2521, 2020. DOI: 10.1109/TITS.2019.2919865.

[240] J. H. Kim, D. S. Kum. Threat prediction algorithm based on local path candidates and surrounding vehicle trajectory predictions for automated driving vehicles. In *Proceedings of IEEE Intelligent Vehicles Symposium*, IEEE, Seoul, Republic of Korea, pp. 1220–1225, 2015. DOI: 10.1109/IVS.2015.7225849.

[241] M. Bošnak, I. Škrjanc. Efficient time-to-collision estimation for a braking supervision system with LIDAR. In *Proceedings of the 3rd IEEE International Conference on Cybernetics*, Exeter, UK, 2017. DOI: 10.1109/CYBConf.2017.7985775.

[242] S. Noh, K. An. Decision-making framework for automated driving in highway environments. *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 1, pp. 58–71, 2018. DOI: 10.1109/TITS.2017.2691346.

[243] M. Y. Yu, R. Vasudevan, M. Johnson-Roberson. Occlusion-aware risk assessment for autonomous driving in urban environments. *IEEE Robotics and Automation Letters*, vol. 4, no. 2, pp. 2235–2241, 2019. DOI: 10.1109/LRA.2019.2900453.

[244] D. Shin, B. Kim, K. Yi, A. Carvalho, F. Borrelli. Human-centered risk assessment of an automated vehicle using vehicular wireless communication. *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 2, pp. 667–681, 2019. DOI: 10.1109/TITS.2018.2823744.

[245] G. F. Li, Y. F. Yang, T. R. Zhang, X. D. Qu, D. P. Cao, B. Cheng, K. Q. Li. Risk assessment based collision avoidance decision-making for autonomous vehicles in multi-scenarios. *Transportation Research Part C: Emerging Technologies*, vol. 122, Article number 102820, 2021. DOI: 10.1016/j.trc.2020.102820.

[246] D. Shen, Y. B. Chen, L. X. Li, S. Chien. Collision-free path planning for automated vehicles risk assessment via predictive occupancy map. In *Proceedings of IEEE Intelligent Vehicles Symposium*, Las Vegas, USA, pp. 985-991, 2020. DOI: 10.1109/IV47402.2020.9304720.

[247] D. Deveaux, T. Higuchi, S. Uçar, C. H. Wang, J. Härri, O. Altintas. Extraction of risk knowledge from time to collision variation in roundabouts. In *Proceedings of IEEE International Intelligent Transportation Systems Conference*, Indianapolis, USA, pp. 3665–3672, 2021. DOI: 10.1109/ITSC48978.2021.9564570.

[248] J. Y. Zhu, Y. L. Ma, Y. N. Lou. Multi-vehicle interaction safety of connected automated vehicles in merging area: A real-time risk assessment approach. *Accident Analysis & Prevention*, vol. 166, Article number 106546, 2022. DOI: 10.1016/j.aap.2021.106546.

[249] X. Li, X. P. Liu. Embedding sustainable development strategies in agent-based models for use as a planning tool. *International Journal of Geographical Information Science*, vol. 22, no. 1, pp. 21–45, 2008. DOI: 10.1080/13658810701228686.

[250] G. D. P. A. Aschwanden, S. Haegler, F. Bosché, L. Van Gool, G. Schmitt. Empiric design evaluation in urban planning. *Automation in Construction*, vol. 20, no. 3, pp. 299–310, 2011. DOI: 10.1016/j.autcon.2010.10.007.

[251] C. D. T. Mathew, P. R. Knob, S. R. Musse, D. G. Aliaga. Urban walkability design using virtual population simulation. *Computer Graphics Forum*, vol. 38, no. 1, pp. 455–469, 2019. DOI: 10.1111/cgf.13585.

[252] T. Feng, L. F. Yu, S. K. Yeung, K. K. Yin, K. Zhou. Crowd-driven mid-scale layout design. *ACM Transactions on Graphics*, vol. 35, no. 4, Article number 132, 2016. DOI: 10.1145/2897824.2925894.

[253] N. Khamis, H. Selamat, F. S. Ismail, O. F. Lutfy. Optimal exit configuration of factory layout for a safer emergency evacuation using crowd simulation model and multi-objective artificial bee colony optimization. *International Journal of Integrated Engineering*, vol. 11, no. 4, pp. 183–191, 2019.

[254] I. Garcia-Dorado, D. G. Aliaga, S. V. Ukkusuri. Designing large-scale interactive traffic animations for urban modeling. *Computer Graphics Forum*, vol. 33, no. 2, pp. 411–420, 2014. DOI: 10.1111/cgf.12329.

[255] B. Haworth, M. Usman, G. Berseth, M. Khayatkhoei, M. Kapadia, P. Faloutsos. CODE: Crowd-optimized design of environments. *Computer Animation and Virtual Worlds*, vol. 28, no. 6, Article number e1749, 2017. DOI: 10.1002/cav.1749.

[256] N. Chakraborty, B. Haworth, M. Usman, G. Berseth, P. Faloutsos, M. Kapadia. Crowd sourced co-design of floor plans using simulation guided games. In *Proceedings of the 10th International Conference on Motion in Games*, ACM, Barcelona, Spain, Article number 1, 2017. DOI: 10.1145/3136457.3136463.

[257] M. L. Xu, Y. P. Wu, P. Lv, H. Jiang, M. X. Luo, Y. D. Ye. miSFM: On combination of Mutual Information and Social Force Model towards simulating crowd evacuation. *Neurocomputing*, vol. 168, pp. 529–537, 2015. DOI: 10.1016/j.neucom.2015.05.074.

[258] J. Tsai, N. Fridman, E. Bowring, M. Brown, S. Epstein, G. A. Kaminka, S. Marsella, A. Ogden, I. Rika, A. Sheel, M. E. Taylor, X. Z. Wang, A. Zilka, M. Tambe. ESCAPES: Evacuation simulation with children, authorities, parents, emotions, and social comparison. In *Proceedings of the 10th International Conference on Autonomous Agents and Multiagent Systems*, Taipei, China, pp. 457–464, 2011.

[259] L. Tan, M. Y. Hu, H. Lin. Agent-based simulation of building evacuation: Combining human behavior with predictable spatial accessibility in a fire emergency. *Information Sciences*, vol. 295, pp. 53–66, 2015. DOI: 10.1016/j.ins.2014.09.029.

[260] S. K. Wong, Y. S. Wang, P. K. Tang, T. Y. Tsai. Optimized evacuation route based on crowd simulation. *Computational Visual Media*, vol. 3, no. 3, pp. 243–261, 2017. DOI: 10.1007/s41095-017-0081-9.

[261] Y. Zang, Q. Mei, S. X. Liu. Evacuation simulation of a high-rise teaching building considering the influence of obstacles. *Simulation Modelling Practice and Theory*, vol. 112, Article number 102354, 2021. DOI: 10.1016/j.simpat.2021.102354.

[262] X. Z. Lu, Z. B. Yang, G. P. Cimellaro, Z. Xu. Pedestrian evacuation simulation under the scenario with earthquake-induced falling debris. *Safety Science*, vol. 114, pp. 61–71, 2019. DOI: 10.1016/j.ssci.2018.12.028.

[263] Z. Q. Wang, G. F. Jia. A novel agent-based model for tsunami evacuation simulation and risk assessment. *Natural Hazards*, vol. 105, no. 2, pp. 2045–2071, 2021. DOI: 10.1007/s11069-020-04389-8.

[264] P. Lv, Q. Zhang, B. Y. Xu, R. Feng, C. C. Li, J. X. Xue, B. Zhou, M. L. Xu. Agent-based campus novel coronavirus infection and control simulation. *IEEE Transactions on Computational Social Systems*, vol. 9, no. 3, pp. 688–699, 2022. DOI: 10.1109/TCSS.2021.3114504.

[265] A. A. Tako, S. Robinson. The application of discrete event simulation and system dynamics in the logistics and supply chain context. *Decision Support Systems*, vol. 52, no. 4, pp. 802–815, 2012. DOI: 10.1016/j.dss.2011.11.015.

[266] Y. Zhang, R. Su, K. Z. Gao, Y. C. Zhang. A pedestrian

hopping model and traffic light scheduling for pedestrian-vehicle mixed-flow networks, [Online], Available: https://arxiv.org/abs/1705.05251, 2017.

[267] B. Li, W. F. Li. Modeling and simulation of container terminal logistics systems using Harvard architecture and agent-based computing. In *Proceedings of Winter Simulation Conference*, IEEE, Baltimore, USA, pp. 3396–3410, 2010. DOI: 10.1109/WSC.2010.5679030.

[268] V. Elia, M. G. Gnoni, F. Tornese. Improving logistic efficiency of WEEE collection through dynamic scheduling using simulation modeling. *Waste Management*, vol. 72, pp. 78–86, 2018. DOI: 10.1016/j.wasman.2017.11.016.

[269] I. H. Zohdy, H. A. Rakha. Intersection management via vehicle connectivity: The intersection cooperative adaptive cruise control system concept. *Journal of Intelligent Transportation Systems*, vol. 20, no. 1, pp. 17–32, 2016. DOI: 10.1080/15472450.2014.889918.

[270] A. S. Kamal, J. I. Imura, T. Hayakawa, A. Ohata, K. Aihara. A vehicle-intersection coordination scheme for smooth flows of traffic without using traffic lights. *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 3, pp. 1136–1147, 2015. DOI: 10.1109/TITS.2014.2354380.

[271] E. Moradi-Pari, H. N. Mahjoub, H. Kazemi, Y. P. Fallah, A. Tahmasbi-Sarvestani. Utilizing model-based communication and control for cooperative automated vehicle applications. *IEEE Transactions on Intelligent Vehicles*, vol. 2, no. 1, pp. 38–51, 2017. DOI: 10.1109/TIV.2017.2708605.

[272] Y. Zhang, Y. C. Zhang, R. Su. Pedestrian-safety-aware traffic light control strategy for urban traffic congestion alleviation. *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 1, pp. 178–193, 2021. DOI: 10.1109/TITS.2019.2955752.

[273] M. K. Heinrich, S. Von Mammen, D. N. Hofstadler, M. Wahby, P. Zahadat, T. Skrzypczak, M. D. Soorati, R. Krela, W. Kwiatkowski, T. Schmickl, P. Ayres, K. Stoy, H. Hamann. Constructing living buildings: A review of relevant technologies for a novel application of biohybrid robotics. *Journal of the Royal Society Interface*, vol. 16, no. 156, Article number 20190238, 2019. DOI: 10.1098/rsif.2019.0238.

[274] X. Lan, Y, Liu, Z. Zhao. Cooperative control for swarming systems based on reinforcement learning in unknown dynamic environment . *Neurocomputing*, vol. 410, no. 3, pp. 10–418, 2020. DOI: 10.1016/j.neucom.2020.06.038.

[275] P. K. Das, H. S. Behera, P. K. Jena, B. K. Panigrahi. An intelligent multi-robot path planning in a dynamic environment using improved gravitational search algorithm. *International Journal of Automation and Computing*, vol. 18, no. 6, pp. 1032–1044, 2021. DOI: 10.1007/s11633-016-1019-x.

[276] Y. Zhao, Y. Ma. Songlin Hu. USV formation and path-following control via deep reinforcement learning with random braking . *IEEE Transactions on Neural Networks and Learning Systems*, vol. 32, no. 12, pp. 5468–5478, 2021. DOI: 10.1109/TNNLS.2021.3068762.

[277] K. Jin, J. Wang, H. Wang, X. Liang, Y. Guo, M. Wang, H. Yi. Soft formation control for unmanned surface vehicles under environmental disturbance using multi-task reinforcement learning. *Ocean Engineering*, vol. 260, Article number 12035, 2022. DOI: 10.1016/j.oceaneng.2022.112035.

[278] K. M. Shi, X. Y. Zhang, S. Xia. Multiple swarm fruit fly optimization algorithm based path planning method for multi-UAVs. *Applied Sciences*, vol. 10, no. 8, Article number 2822, 2020. DOI: 10.3390/app10082822.

[279] F. A. De Alcantara Andrade, A. R. Hovenburg, L. N. De Lima, C. D. Rodin, T. A. Johansen, R. Storvold, C. A. M. Correia, D. B. Haddad. Autonomous unmanned aerial vehicles in search and rescue missions using real-time cooperative model predictive control. *Sensors*, vol. 19, no. 19, Article number 4067, 2019. DOI: 10.3390/s19194067.

[280] P. Yao, H. L. Wang, H. X. Ji. Multi-UAVs tracking target in urban environment by model predictive control and improved grey wolf optimizer. *Aerospace Science and Technology*, vol. 55, pp. 131–143, 2016. DOI: 10.1016/j.ast.2016.05.016.

[281] J. F. Wu, H. L. Wang, N. Li, P. Yao, Y. Huang, Z. K. Su, Y. Yu. Distributed trajectory optimization for multiple solar-powered UAVs target tracking in urban environment by adaptive grasshopper optimization algorithm. *Aerospace Science and Technology*, vol. 70, pp. 497–510, 2017. DOI: 10.1016/j.ast.2017.08.037.

[282] X. F. Wang, H. Zhao, T. Han, H. Zhou, C. Li. A grey wolf optimizer using Gaussian estimation of distribution and its application in the multi-UAV multi-target urban tracking problem. *Applied Soft Computing*, vol. 78, pp. 240–260, 2019. DOI: 10.1016/j.asoc.2019.02.037.

[283] R. N. Mohd, J. Geraghty. Genetic algorithm performance with different selection strategies in solving TSP. In *Proceedings of the World Congress on Engineering*, International Association of Engineers, London, UK, 2011.

[284] S. T. Roberts. Commercial content moderation: Digital laborers' dirty work. *The Intersectional Internet: Race, Sex, Class and Culture Online*, S. U. Noble, B. M. Tynes, Eds., Pieterlen, Switzerland: Peter Lang Publishing, 2016.

[285] A. Ponsich, A. L. Jaimes, C. A. C. Coello. A survey on multiobjective evolutionary algorithms for the solution of the portfolio optimization problem and other finance and economics applications. *IEEE Transactions on Evolutionary Computation*, vol. 17, no. 3, pp. 321–344, 2013. DOI: 10.1109/TEVC.2012.2196800.

[286] M. R. AlRashidi, M. E. El-Hawary. A survey of particle swarm optimization applications in electric power systems. *IEEE Transactions on Evolutionary Computation*, vol. 13, no. 4, pp. 913–918, 2009. DOI: 10.1109/TEVC.2006.880326.

[287] A. Ouaarab, B. Ahiod, X. S. Yang. Discrete cuckoo search algorithm for the travelling salesman problem. *Neural Computing and Applications*, vol. 24, no. 7–8, pp. 1659–1669, 2014. DOI: 10.1007/s00521-013-1402-2.

[288] E. Osaba, X. S. Yang, F. Diaz, P. Lopez-Garcia, R. Carballedo. An improved discrete bat algorithm for symmetric and asymmetric traveling salesman problems. *Engineering Applications of Artificial Intelligence*, vol. 48, pp. 59–71, 2016. DOI: 10.1016/j.engappai.2015.10.006.

[289] Y. Huang, X. N. Shen, X. You. A discrete shuffled frog-leaping algorithm based on heuristic information for traveling salesman problem. *Applied Soft Computing*, vol. 102, Article number 107085, 2021. DOI: 10.1016/j.asoc.2021.107085.

[290] E. Summers, R. Punzalan. Bots, seeds and people: Web archives as infrastructure. In *Proceedings of ACM Con-*

ference on Computer Supported Cooperative Work and Social Computing*, Portland, USA, pp. 821–834, 2017. DOI: 10.1145/2998181.2998345.

[291] S. Seidel, N. Berente, A. Lindberg, K. Lyytinen, J. V. Nickerson. Autonomous tools and design: A triple-loop approach to human-machine learning. *Communications of the ACM*, vol. 62, no. 1, pp. 50–57, 2019. DOI: 10.1145/3210753.

[292] W. Shi, W. N. Chen, Y. Lin, T. L. Gu, S. Kwong, J. Zhang. An adaptive estimation of distribution algorithm for multipolicy insurance investment planning. *IEEE Transactions on Evolutionary Computation*, vol. 23, no. 1, pp. 1–14, 2019. DOI: 10.1109/TEVC.2017.2782571.

[293] M. Asafuddoula, T. Ray, R. Sarker. A decomposition-based evolutionary algorithm for many objective optimization. *IEEE Transactions on Evolutionary Computation*, vol. 19, no. 3, pp. 445–460, 2015. DOI: 10.1109/TEVC.2014.2339823.

[294] H. D. Wang, Y. C. Jin, J. Doherty. Committee-based active learning for surrogate-assisted particle swarm optimization of expensive problems. *IEEE Transactions on Cybernetics*, vol. 47, no. 9, pp. 2664–2677, 2017. DOI: 10.1109/TCYB.2017.2710978.

[295] C. D. Fjell, H. Jenssen, W. A. Cheung, R. E. W. Hancock, A. Cherkasov. Optimization of antibacterial peptides by genetic algorithms and cheminformatics. *Chemical Biology & Drug Design*, vol. 77, no. 1, pp. 48–56, 2011. DOI: 10.1111/j.1747-0285.2010.01044.x.

Hua Wang received the Ph. D. degree in computer science from Institute of Computing Technology, Chinese Academy of Sciences, China in 2015. She is currently an associate professor of Zhengzhou University, China.

Her research interests include traffic animation and environment modeling.

E-mail: iewanghua@zzu.edu.cn

ORCID iD: 0000-0001-9072-6638

Xing-Yu Guo received the B. Sc. degree in software engineering from the College of Data Science, Taiyuan University of Technology, China in 2021. She is currently a Ph. D. degree candidate in software engineering at School of Computer and Artificial Intelligence, Zhengzhou University, China.

Her research interest is collective movement simulation evaluation.

E-mail: guoxingyu@gs.zzu.edu.cn

Hao Tao received the Ph. D. degree in control science and engineering from Xi′an Jiaotong University, China in 2015. He is currently a senior engineer of China Ship Development and Design Center, China.

His research interests include swarm intelligence and digital twin.

E-mail: chst722@163.com

Ming-Liang Xu received the Ph. D. degree in computer science and technology from State Key Laboratory of CAD and CG, Zhejiang University, China in 2012. He is currently a professor with School of Computer and Artificial Intelligence, Zhengzhou University, China. He has authored more than 60 journal articles and conference papers in these areas, including *ACM Transactions on Graphics*, *IEEE Transactions on Pattern Analysis* and *Machine Intelligence*, *IEEE Transactions on Image Processing*, *IEEE Transactions on Circuits and Systems for Video Technology*, *ACM Special Interest Group on Computer Graphics*, *Asia ACM Multimedia Conference*, and *IEEE International Conference on Computer Vision*.

His research interests include computer graphics, multimedia and artificial intelligence.

E-mail: iexumingliang@zzu.edu.cn (Corresponding author)

ORCID iD: 0000-0002-6885-3451

Citation: H. Wang, X. Y. Guo, H. Tao, M. L. Xu. Collective movement simulation: methods and applications. *Machine Inteligence Research*, vol.21, no.3, pp.452–480, 2024. https://doi.org/10.1007/s11633-022-1405-5