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Simulation en temps réel de planification d'une foule d'humains virtuels

Real time simulation of virtual human crowd planning

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Résumé

Abstract

Behavioral simulation consists to simulate and animate virtual environments populated by virtual humans, and focuses both on local and global realism.

For this reason, the simulation of pedestrians crowd is widely used by several domains such as the film industry, video games, security, civil engineering, urban planning ... etc.

To simulate realistic crowds of virtual humans in real time, three main requirements need satisfaction. First of all,

efficiency is essential, the simulation model must make it possible to simulate crowds in an efficient way in terms of computational cost. Secondly, quantity, that is to say, the ability to simulate thousands of characters, finally realism, which means the need to identify the interactions between each individual and his neighborhood and then influence the individual behaviors, and to reproduce some macroscopic phenomena.

Proposing a solution able to manage all these three aspects is a challenging problem that we have addressed in this thesis.

In this thesis, we develop a hybrid architecture to perform crowd behavior simulation in order to simultaneously satisfy the criterion of macroscopic and microscopic realism, while ensuring path planning and dynamic avoidance of collisions for large numbers of pedestrians.

This architecture consists to divide the simulation environment into exhaustive regions, where motion modeling is managed by two approaches of different levels of detail.

Concretely, the high-density regions are governed by a macroscopic approach based on a flow potential to generate macroscopic phenomena, while the other zones use a microscopic method to perform individual behaviors.

Our architecture also allows to ensure the continuity of movements during a change between two algorithms.

Keywords.

Virtual crowds, real-time, motion simulation, behavior, macroscopic simulation, microscopic approach.

Résumé

La simulation comportementale cherche à simuler et animer des environnements virtuels qui sont généralement peuplés d'humains virtuels, et s'intéresse surtout au réalisme local et au réalisme global.

Pour cette raison, la simulation de la foule des piétons est largement employée par de nombreuses domaines d'applications tels que l'industrie du cinéma, du jeu vidéo, la sécurité, le génie civil, l'urbanisme...etc.

Afin de simuler des foules d'humains virtuels en temps réel et de manière réaliste, trois éléments principaux doivent être réunis. Premièrement l'efficacité est primordiale, le modèle de simulation doit permettre de simuler des foules de manière efficace en terme de coût calculatoire. Deuxièmement la quantité, c'est-à-dire la capacité de simuler des milliers de personnages, finalement le réalisme, ce que signifie la nécessité d'identifier les interactions entre chaque individu et son voisinage pour ensuite influencer le comportement de l'individu, et de reproduire certains phénomènes macroscopiques. La proposition d'une solution capable de gérer ces trois aspects est un problème intéressant et stimulant que nous avons adressé dans cette thèse.

Dans le cadre de cette thèse, nous développons une architecture hybride pour effectuer des simulations comportementales de foules, pour pouvoir satisfaire simultanément les deux types de réalisme macroscopique et microscopique et rendre compte la planification de chemins et l'évitement dynamique de collisions pour de grand nombre de piétons. Cette architecture consiste à diviser l'environnement de simulation en des zones exhaustives, où la modélisation de mouvement est gérée par deux approches de différents niveaux de détail.

Concrètement, les régions de haute densité sont gouvernées par une approche macroscopique basée sur un flux de potentiel pour générer des phénomènes macroscopiques, tandis que les autres zones exploitent une méthode microscopique pour réaliser des comportements individuels. Notre architecture permet aussi d'assurer la continuité de mouvements lors d'un changement entre deux algorithmes.

Mots clés.

Foules virtuelles, temps-réel, simulation de mouvements, comportement, macroscopique simulation, microscopique approche.

الملخص

إن محكاه دينامية المشاة تسعي إلي تنشيط الوسائط الافتراضية التي تكون عادة مأهولة بالناس، وتهتم بشكل خاص بالتركيز في نفس الوقت على الواقعية الدقيقة و الشاملة.

لهذا السبب،فان محاكاة المشاة تستخدم على نطاق واسع في العديد من مجالات مثل صناعة الأفلام، والألعاب، والأمن، والهندسة المدنية، والتخطيط الحضري ... الخ

لكي يتم تنفيذ محاكاة بطريقة أكثر واقعية و في الوقت زمني قصير, هناك ثلاثة عناصر رئيسية يجب مراعاتها.

أولا الكفاءة، يجب أن يكون نموذج المحاكاة قادرا علي تحقيق محاكاة المشاة بكفاءة من حيث التكلفة الحسابية. ثانيا الفاعلية، وهذا يعني القدرة على محاكاة الآلاف من الشخصيات الافتراضية. و أخيرا الواقعية، وهو ما يعني الحاجة إلى تحديد التفاعلات بين الفرد ومحيطه ثم التأثير على سلوكيات الفردية، إضافة إلي إظهار الظواهر الجماعية.

اقتراح و تقديم حل قادر علي إدارة هذه الجوانب الثلاثة سيتم التطرق له في هذا البحث.

في مضمون هذه الأطروحة، سيتم اقتراح بنية مركبة لأداء المحاكاة سلوكيات الحشود، من أجل تحقيق كلا النوعين من الواقعية العيانية والمجهرية في نفس الوقت. إضافة إلي توجيه المشاة بناءا علي تحديد الاتجاهات و المسارات.

النموذج المقترح يركز علي تقسيم الوسط إلي مناطق متباينة، حيث يتم محاكاة دينامية المشاة عن طريق دمج طريقتين من مستويات مختلفة الدقة.

على وجه التحديد، تخضع المناطق عالية الكثافة لطريقة محاكاة منخفضة الدقة لاضهار عينات من السلوكيات الجماعية، في حين أن مناطق أخرى تعمل على طريقة محاكاة عالية الدقة لتحقيق السلوك الفردي.

كما يضمن النموذج المقترح استمرارية الحركة عند تغيير بين اثنين من طرق المحاكاة.

الكلمات الرئيسية.

حشود افتراضية، وقت تنفيذ حقيقي, محاكاة الحركة, سلوكيات, طريقة محاكاة منخفضة الدقة, طريقة مجهرية.

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I would like to thank my supervisor, Professor CHERIF Foudil for his great help and support during my research studies and especially for his valuable advice in the theoretical and practical parts of this work.

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Contents

List of Tables

Introduction

A crowd can be defined as a situation where humans flock together like other aggregations of animals (e.g. herds of cattle and schools of fish) or material (e.g. fluid and particle flow). A crowd can also be defined as a large group of individuals in the same physical environment and sharing a common goal. Crowds can occur in many places including for example train stations, shopping malls and stadia.

Crowds have become an important research area for many scientists since the nineteenth century. In particular, from the perspective of computer graphics research, Crowd simulation is the process of simulating large numbers of humans, or agents, in one environment. The task is challenging because human crowds exhibit highly complex behavior driven by individual decisions of agents with respect to their goals, obstacles, and other nearby agents.

Crowd simulation is an active area of research that finds several applications in the design of urban environments and the development of emergency evacuation strategies [1]. Crowd simulation also finds itself broad application in entertainment industry. In movie production and computer games, large numbers of characters need to be animated. The effect of simulation greatly influences the realism of scene and the experience of interaction.

Several models for crowd simulation have been proposed and many efforts have been made to modulate intuitive navigation control and real time crowd behavior simulation, these models were classified into two categories: microscopic and macroscopic. Macroscopic models look at the simulated crowd as a whole, focus on the flow characteristics instead of the individual behaviors of the pedestrians. Microscopic models are the opposite. They study the behavior of the individual pedestrians and their interactions with other peers in the crowd. These allow to animate virtual crowds of agents with realistic autonomous behaviors. Perception and placement are defined for every agent resulting in a richer and more complex simulation. There are two conflicting requirements in crowd simulation.

Introduction

The first major problem is that the most applications require a human crowd simulated in real time, with higher level of detail and an accurate realism of behaviors. Then, there is still a clear relationship between the accuracy realism of crowd behaviors and the computational costs of simulation. Satisfying these both constraints at the same time is particularly a challenge of great importance. The majority of the previous models have a limited ability to response to the latter problem, they tend to focus on a single factor; there is no existing method that is able to reduce the computational cost while maintaining the high level detail of simulation [2, 3]. Almost all the existing models were agent-based (microscopic models). This approach describes the most natural way to simulate crowds as independent autonomous pedestrians interacting with each other; it usually handles local collision avoidance and global navigation for each person. However, these kinds of models have the drawback that when animating a large crowd, they are computationally intensive. Microscopic models give more accurate results only for smaller crowds to achieve real time simulation. On the contrary, the macroscopic models are usually created to realize a real time simulation for very large crowds; they follow the features of the flow as long as the overall crowd behavior seems realistic. These models offer a coarse-grained simulation result with higher execution efficiency which is due to the lack of concerns on individual issues [4].

Finally, modeling the movement and behavior of the virtual crowd remains a major challenge as highly dynamic complex systems, the crowd is a large group of pedestrians with non-uniform spatial distribution and heterogeneous behavior characteristics, and it exhibits often distinct characteristics, such as independent behaviors, self-organization, and pattern formation, due to interactions among the individuals. Previous works have suggested that human crowd dynamic can be modeled on many different scales, from coherent aggregate behaviors of the crowd on the largest scales to the individual behaviors, interactions among individuals on the small-scale detail. Such multi-scale systems are computationally expensive for traditional simulation techniques to capture over the full range of scales.

To overcome these two conflicting goals, we assume a scalable simulation is required to handle at least several hundreds or even thousands of pedestrians, running in real-time, particularly with respect to the complexity of the environment and the realism of behaviors required by the crowd, we investigate to find a good balance between visual credibility of complex crowd behaviors and computational requirements, where the behaviors of human crowd can be viewed on a two different level of detail: from the chaotic, fluctuating interactions between individual objects on the finest scales, to the coherent aggregate flow of the pedestrian crowd on the largest scales.

Our solution consists to introduce a hybrid simulation architecture that combines the strengths of two classes of crowd modeling to achieve flexible, interactive, high-fidelity simulation on large environment. This architecture couples a microscopic model of individual navigation with a novel continuum approach for the collective motion of pedestrians; it can apply to simulate the behaviors and movement patterns of extremely large crowds at near real-time rates on commodity hardware.

Our approach is able to determine by itself the most suitable model of modeling for each region in the environment, regarding the simulation context, in real time and within a continuous environment. To do so, we first introduce the generic notions of dynamic change of representation, and we describe our method for handling the transfer of pedestrian between continuum and discrete simulation areas and discuss how the constituent simulation components are adapted to handle this transition.

Then, we evaluate this approach experimentally along two criteria: the impact of our methodology on the computational resources, and an estimation of the dissimilarity between a full microscopic simulation and a simulation with our methodology. Finally we discuss the results obtained and propose enhancements for future works.

This thesis consists of seven chapters, each of which is broken down into a number of sections and subsections that present the research in detail. The content of each chapter is summarized as follows:

- ✓ Chapter 1. This chapter starts with the literature survey about general issues in crowd simulation. This is followed by the detailed summary of navigation process and group behaviors.
- ✓ Chapter 2 includes a comprehensive review of crowd modeling and simulation within the scope of this research study. It introduces different aspects of crowd simulation and its relationship to crowd modeling, followed by detailed reviews on crowd modeling approaches, and typical crowd models and their represented crowd behaviors.

- ✓ Chapter 3. To fully understand our contributions in this research, we detail and explain the background that represents the proposed techniques to path planning, decision making and collision avoidances and their supporting foundations.
- ✓ Chapter 4. describes a hierarchical navigation model to describe the movements of a pedestrian. During the simulation process, each virtual pedestrian needs to select a goal as its destination the macro-level navigation model is used to compute a path (not necessary shortest) to a destination based on various influences that may affect route choice.
- ✓ Chapter 5. presents the construction of the macroscopic model and its application to simulate pedestrian dynamics. This model includes three major components: (i) a proposed speed-density relationship; (ii) determination of the directions of motion of the pedestrians by using an eikonal equation; and (iii) the mass conservations equation to describe the time evolution of crowd density.
- ✓ Chapter 6. In this Chapter, we describe our hybrid framework for simulating the movement of crowds. The macroscopic and behavioral models are introduced and implemented. We describe a strategy that allows dealing with the interaction and the online-switching of simulation models for crowd behaviors studying.
- ✓ Chapter 7. To complete our crowd simulation model, we have implemented several techniques allowing to avoid inter-pedestrian collisions in the short-term. This Chapter presents these methods, their functioning, and their implementation.
- ✓ Finally, the conclusion section outlines the directions for future work.

Chapter 1 Behavioral Simulation for Virtual Crowd

1. Introduction

Crowd simulation has a wide range of application areas from computer games to evacuation planning for building security. The topic has drawn the attention of computer graphics and visualization community as well as cognitive science and artificial intelligence researchers. Since a human being is a complex structure, masses of human beings should be even more complicated to study. When humans form groups, interaction becomes an essential part of the overall group behavior. In some cases, individuality gets lost and collective behavior comes on the scene. The semantics underlying the motion of real crowds should be studied extensively in order to achieve realistic behavior in virtual ones. Therefore, crowd simulation research also benefits from social psychology literature.

This chapter focuses on definition of a crowd, and its types, it provides an overview of previous work that has been achieved in the domain of real-time crowd simulations. Some empirical data of pedestrian dynamics and examples of self-organized patterns forming in pedestrian crowds are described in section 4. Subsequently, we present in detail the related work in the domain of crowd behaviors (section 5), navigation (section 6) and group behaviors (section 7). Finally, conclusion of this chapter is given in section 8.

2. How is Crowd Defined?

In the field of crowd research, the definitions of 'crowd' evolve around all the situations where a number of people gathers in a rather small area and interacts with each other [5]. Several authors in the literature use the word crowd as a description for a multitude of individuals walking through the same space at a certain moment in time.

According to Le Bon [6], crowds are much more than the physical presence of the individuals who comprise them; a crowd is best defined as a psychological occurrence rather than a physical one. Le Bon referred to a psychologically defined crowd as an organized crowd in which the individuals comprising the crowd in essence lose their individuality and become one organized being with the characteristics of the individuals lost to the characteristics of the crowd. This loss of individuality is key to the formation of a psychologically defined crowd; a psychologically defined crowd is neither a matter of quantity nor the coincidental simultaneous gathering of multitudes. "A thousand individuals accidentally gathered in a public place without any determined object in no way constitutes a crowd from the psychological point of view" [6].

In [5], "A crowd is a large group of individuals ($\mathrm{N} \geq 100$ Persons) within the same space at the same time whose movements are for a prolonged period of time ($\mathrm{t} >= 60\,s$) dependent on predominantly local interactions ($\mathrm{k} \geq 1\ \mathrm{P/m^2}$)". The numbers N (number of individuals), k (density) and t (time) are chosen in a way as to exclude movements during which interaction is non-existent or only present for very short periods of time. Even when using the definition above the sort of crowds within the spectrum might differ greatly.

According to empirical data gathered by scientists, crowds are more of a process (see Fig. 1.1)- they have a beginning, middle and end [7].

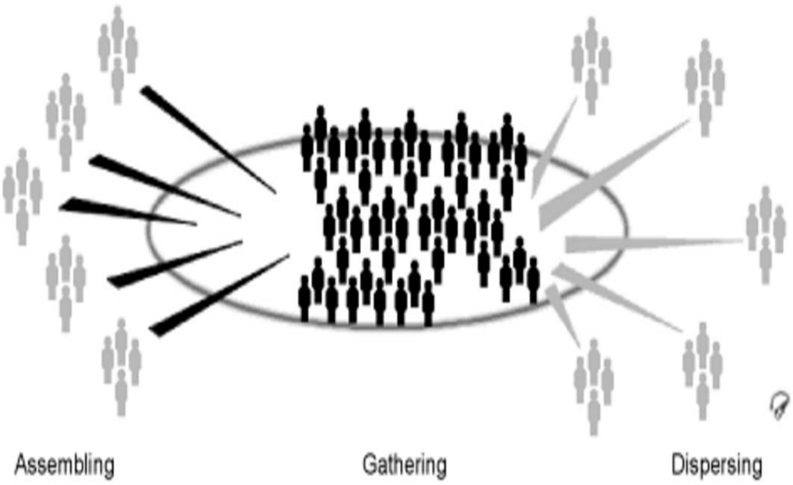


Figure 1. 1 Crowd is a process of assembling, gathering and dispersing [7].

- ✓ The Assembling Process refers to the movement of people from different locations to a common location, within a given period of time. It largely determines who participates in a gathering.
- ✓ The Temporary Gathering: refers to the collection of individuals and small groups in a common location. It is the result of the assembling process. The temporary gathering consists of the individual and collective actions.

- ✓ The Dispersing Process. This is the last phase in the life of a temporary gathering. It involves the movement of people from a common location to one or more alternate locations. Dispersal brings the temporary gathering to an end, or at least begins its decline. Dispersal can occur on a routine, emergency and coerced basis.

3. Types of Crowd

There is a scarcity of research literature in this context of crowd characterization. Starting with more generic crowd types:

In his prominent article, R. W. Brown [8] uses the term collectivity for two or more people who can be discussed as a category. He defines crowds as collectivities that congregate on a temporary basis. Since the reasons that bring crowd members together are various, Brown classifies them in terms of the dominant crowd behavior. He gives a detailed taxonomy of crowds, but basically, he classifies them into two: mobs and audiences. Audiences are passive crowds, who congregate in order to be affected or directed, not to act. Mobs, on the other hand, are active crowds. In fact, the word mob is derived from the word “mobile”. There are different tendencies among mobs and audiences. Fig. 1.2 shows Brown’s taxonomy of crowds.

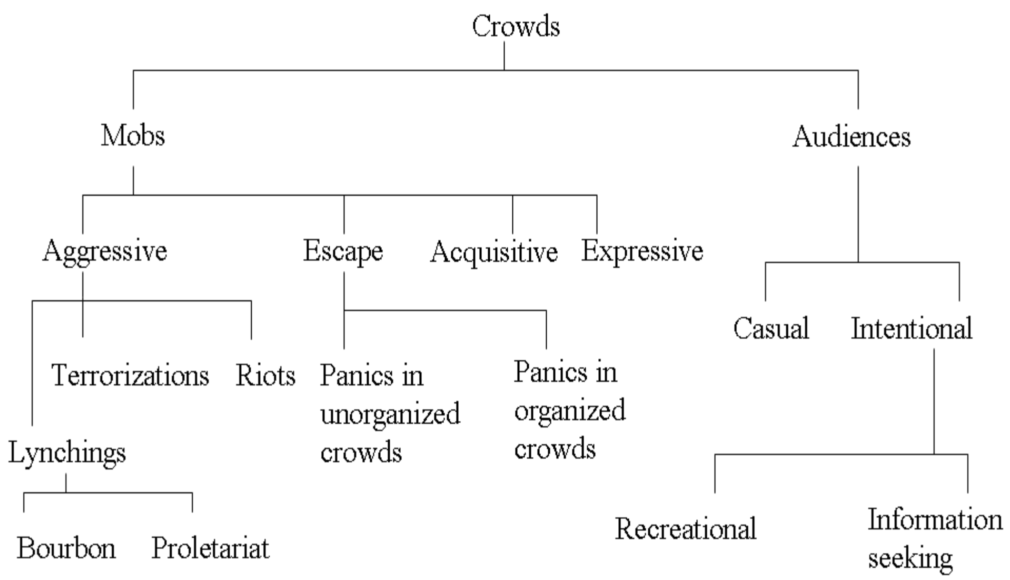


Figure 1. 2 Mass phenomena from Brown [8].

According to the classification, mobs are further divided into four groups. They can be aggressive, escape, acquisitive or expressive crowds. It is not always clear into which category a disturbance falls. Aggressive mobs are defined by anger. Lynchings are directed against individuals, whereas terrorizations are directed against groups. Riots are directed against a collectivity and they are urban as opposed to Lynchings and terrorizations, which are rural disturbances.

Escape crowds are defined by fear. They are panicking crowds, which can be unorganized or organized as in armies. Acquisitive mobs are centripetal and they converge upon a desired object. For example, hunger riots, looting shops and houses are all performed by acquisitive mobs. Finally, expressive mobs congregate for expressing a purpose, such as strikes, rallies, festivals or parades. Similar to mobs, audiences are also classified further. Casual audiences are groups of people who temporarily become polarized through their interest in an event.

People gathering around an interest point out of curiosity is an example of casual audiences. Intentional audiences can be either recreational or information seeking. People in a movie theater are examples of recreational audiences whereas people attending classes are examples of information seeking audiences.

Momboisse (1967) [9] distinguishes four types of crowd:

- ✓ Casual crowds – i.e., ones which are not organized or unified, but comprise individuals who are simply in the same place at the same time.
- ✓ Conventional crowds – i.e., ones which are gathered for a specific purpose or to observe a specific event, with crowd members who share common interests.
- ✓ Expressive crowds – i.e., ones with members who are involved in some form of non-destructive and organized expressive activity such as singing and dancing.
- ✓ Aggressive Crowd, in which members of the crowd are engaged in an unorganized destructive activity such as a looting mob.

4. Empirical observations

Empirical data of pedestrian dynamics provides significant insights into the characteristics and the walking behavior of individuals and human crowds. It used to understand the several collective phenomena of the pedestrian dynamics.

Some previous findings, however, has been done specifically in the field of pedestrian crowds dynamics, but a real extensive summary was done the first time by Helbing [10]. They studied many self-organization phenomena on the base of observations, photographs and time-lapse movies. The idea is to understand deeply the dynamics of the pedestrian in order to recreate a mathematical model able to reproduce these features in a realistic way. This gives the possibility to study different other cases in an easier and more economic way, indeed computer simulations are a really powerful tool for designing and planning pedestrians facilities.

In this section the empirical results will be described. The empirical study is not only important for the creation of the model but also for applications like safety study and legal regulations.

4.1. Behavior in normal situations

Though the dynamics of the pedestrians can be sometimes chaotic and irregular, it is possible to find some regularities and rules, some of which become more visible in time-lapse films. The following list is a summary result of some other pedestrians studies and observations [11, 10]:

- ✓ Pedestrians prefer to walk with an individual pedestrian speed, that normally is the least energy consuming and comfortable one. Normally this speed is the minimum one in order to arrive to the destination in time. Considering that the speed of walking within pedestrian crowds depends on the situation, age, sex, purpose of the trip, time of the day, etc.
- ✓ Pedestrians always try to find the shortest and easiest way to reach their destination. If possible they avoid detours, even if the shortest way is crowded. The basic principle is the "least effort principle", which means everyone tries to reach his goal as fast as possible though spending the least amount of energy and in this example time.
- ✓ Normally humans prefer not to get to close to the people around them. Everyone has is personal comfort zone, which he tries to protect if possible. This distance is smaller if the pedestrian is in hurry and with the increase of the pedestrians density.

  Another interesting observation is that individuals knowing each other can form a group that behaves like a single pedestrian. Some studies modeled the size of groups as a Poisson distribution.

- ✓ Pedestrian always act more or less automatically, even if the situation is new. An example of this behavior are pedestrians that cause delays or obstructions, by entering a train or an elevator before other pedestrians went out of them.

4.2. Behavior in panic situations

Typically "panic situations" are those, where people compete for scarce or dwindling resources (e.g. safe space and access to an exit), which leads to selfish, a social or even irrational behaviors and contagion that affects large groups. This phenomena is understandable in life threatening situations, like a fire in a crowded building, but sometimes it occurs even in unreasonable situations like in cases of a rush for good seats at concerts.

As mentioned before it is difficult to understand this behavior, but some features appear to be typical [10]:

- ✓ Obviously people try to leave the building as fast as possible, therefore they move considerably faster than in normal situation.
- ✓ The more nervous people get, the less they care about their comfort zone and about finding the most convenient and shortest way. It is observable, that for example, if people have to leave a building in an emergency situation and they don't know the structure of the building well enough, they would run for the exit they used as an entrance, even if other exits might be easier to reach or even safer. They also might lose the ability to orient themselves in their surrounding and thus show herding or flocking behavior.
- ✓ Individuals start to exhibit new characteristics like pushing or other physical interactions. Those are often responsible for major injuries or great amounts of injured or even dead due to the forces generated by people crowds.
- ✓ Furthermore people who stumble or fall down create new obstacles for following people, which can again slow down the evacuation.

4.3. Crowd movement base cases

At the beginning the different motion base cases the models should be able to model will be described. Some of these are common from everyday experience. This will be an initial benchmark test for the models used. The movement base cases combined cover the whole range of pedestrian movement behavior. Within this discussion eight distinct motion base cases where determined [5].

Fig. 1.3. presents a nested structure describing the crowd movement base cases. Fig. 1.4. subsequently shows the eight resulting crowd movement base cases which together represent a large range of crowd movement situations.

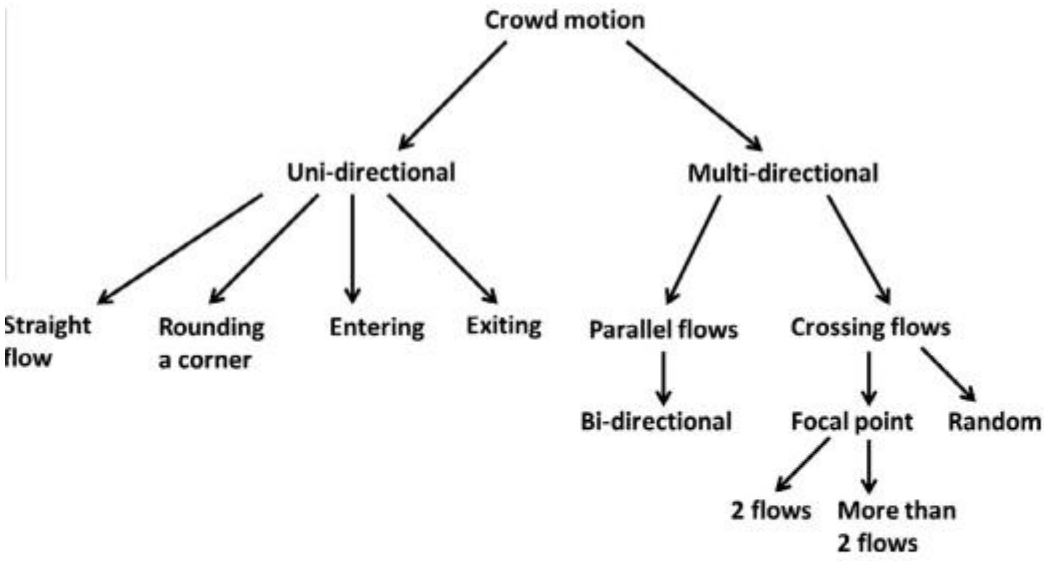


Figure 1. 3 Taxonomy crowd movement base cases [5].

First of all, a distinction can be made between uni-directional and multidirectional flows. Uni-directional flows can either be straight flows (see Fig.1.4. A – no changes in available space or changes in direction), flows rounding corners (Fig.1.4. B – change in direction), flows entering a bottleneck (Fig.1.4. C – decrease of available walkway width) or flows exiting a bottleneck (Fig. 1.4. D – increase of available walking space).

Multi-directional flows (≥ two directions) can either be parallel or intersection under an angle. In parallel flows bi-directional flows will occur (Fig.1.4. E). In the latter case (intersecting flows) the exact occurring movement pattern depends on the available space and the number of flows present at the intersection. The interaction of the streams might cause a random crossing situation (Fig.1.4. H), where a lot of consecutive 2-person crossings will happen shortly after each other, or the situation where the pedestrians intersect at a focal point. Depending on the number of flows intersecting at the focal point, distinct types of behavior emerge. Two (Fig.1.4. F) or more-directional flows (Fig.1.4. G) are therefore separately assessed in the comparison of the models.

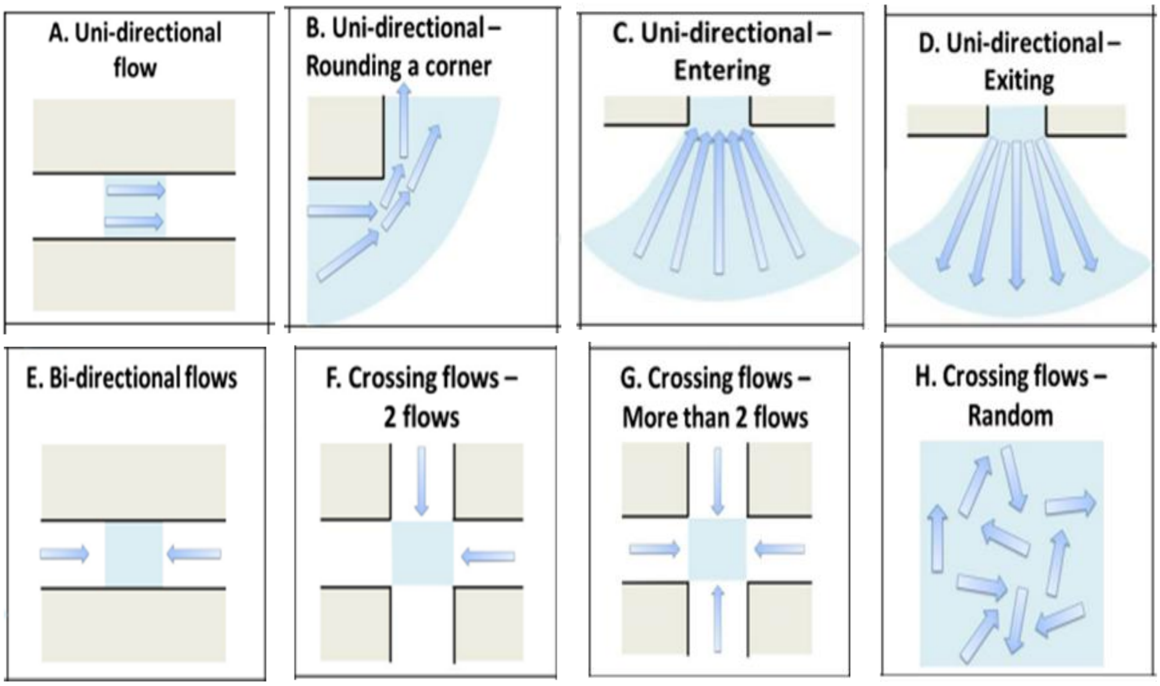
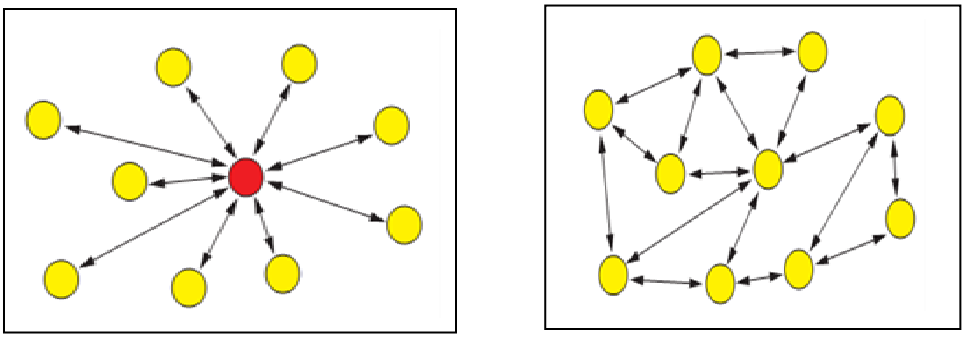


Figure 1. 4 Visualization of crowd movement base cases [5].

4.4. Crowd Self-Organization Phenomena

Self-organization is defined as the spontaneous emergence of a global structure that is triggered by local interactions between members of a system. Self-organization phenomena are macroscopic effects reflecting the pedestrians' microscopic interactions.

A crowd is "organized" when a leader (can be a unique member or a small group of individuals) collects the information provided by all the members of the group, analyzes it, makes its decision, and transmits its instructions back to the members (Fig.1.5 (a)). Instead, a crowd is "self-organized" when a coordinated spatial distribution arises by simply applying some local behavioral rules or one-to-one interactions among pedestrians. In this case, each individual is independent, all are interconnected by a vast network of interactions as illustrated in Fig.1.5. (b), It has its own unique information depending on its position within the group. Then by interacting with its surrounding, the information is locally exchanged [4].



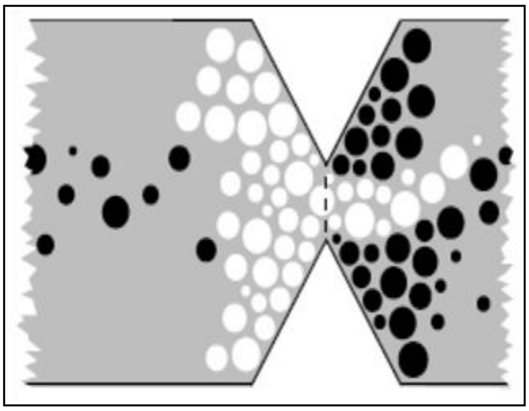
(a) (b)

Figure 1. 5 Two systems using (a) a centralized and (b) a decentralized mechanism [4].

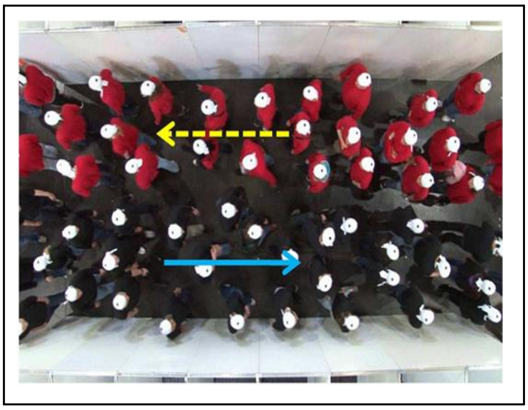
Several studies describing the behavior of pedestrian and its collective motion in a crowd include both qualitative (e.g., the determination of pedestrians' preferences) and quantitative (e.g., the walking speed of pedestrians) observations. These observations allow us to list certain behavioral characteristics of pedestrians as well as highlight and describe several phenomena of a crowd's self-organization that occur in certain specific situations.

- ✓ Jamming and clogging [11]: typically occur for high densities at locations where the inflow exceeds the capacity. Locations with reduced capacity are called bottlenecks. This kind of jamming phenomenon does not depend strongly on the microscopic dynamics of the particles. Rather it is a consequence of an exclusion principle: space occupied by one particle is not available for others. Other types of jamming occur in the case of counter-flow where two groups of pedestrians mutually block each other. This happens typically at high densities and when it is not possible to turn around and move back, e.g. when the flow of people is large.
- ✓ Lane formation (Fig. 1.6 (b)): In bidirectional flows, pedestrians automatically start forming a number of lanes of varying width, with people in each lane moving in the same direction [12].
- ✓ Freezing-by-heating effect [11]. In counter-flows, at sufficiently high densities, lanes are destroyed by the increasing fluctuation strength (which is similar to the temperature). However, instead of the expected transition from the "fluid" lane state to a disordered, "gaseous" state, a solid state is formed. This is characterized by a blocked situation.

- ✓ Oscillations at bottlenecks [11] (Fig. 1.6 (a)). Most existing pedestrian models show exhibit oscillations at bottlenecks when two crowds moving in opposite directions meet at an exit. Once a pedestrian manages to make his way through the opposing group, he is immediately followed by others of his side. While individuals are waiting on the other side, pressure starts building up until they manage to cut the opposing flow and force their passage.



(a) Oscillations of the passing direction at a bottleneck [11]



(b) Lane formation observed during an experiment on bidirectional pedestrian flow [4]

Figure 1. 6 Self-organization behaviors.

5. Virtual Character Behavior Modeling

Modeling of realistic human behavior in general is considered as challenging task matter since each human has different characteristics and there are many factors affecting human behavior. There are also difficulties in developing human behaviors that are believable and reflect on the real world behavior of humans. There have been different approaches and studies developing to model and simulate this pedestrian behavior in virtual worlds, but no method has been proven to be the best. The choice mostly depends on the goals and priorities of the study. Several approaches are presented in this section.

In [13], a virtual agent simulation platform is proposed to develop and visualize in real– time the behavior for thousands of agents. It is based on the concept of a 2D grid (Fig. 1.7). The 2D grid is composed of cells on which the agents navigate. The pedestrians behaviors are defined with a four-layered structure, each layer reflects a different aspect of an agent's behavior. The two first layers are used to compute the collision detection against the environment and other agents and the last two are used for more complex behaviors. The layers are described as follows:

- ✓ ***Inter-collision detection layer***: responsible for agent-agent collision detection. When an agent wishes to move to a particular cell, it verifies that the target cell is free.
- ✓ ***Collision detection layer***: This layer defines which areas on the grid are accessible to the agents. This is achieved by providing an input image, used as a height or collision map, to determine accessible areas on the grid.
- ✓ ***Behaviors layer***: This layer represents more complex behavior. By using a color map as an input file, and associating each color with a particular behavior, an agent can decide which action to perform based on the encoded color. Examples of behavior represented at this layer would be waiting or turning left.
- ✓ ***Callback layer:*** This final layer represents actions that an agent may perform to interact directly with the environment. Examples of this type of behavior might be an agent pushing a button at a particular location.

The combination of these four layers permits the creation of complex behaviors that can appear extremely realistic but can be still executed at interactive rates [13].

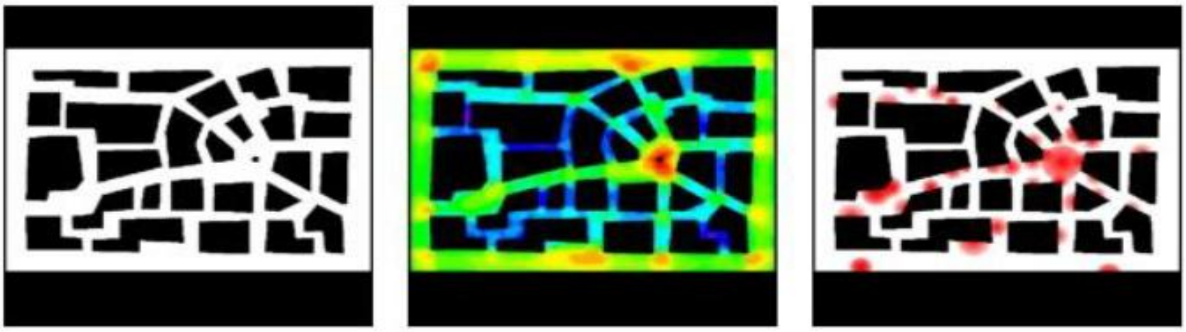


Figure 1. 7 Collision map (black and white), Behavior maps (color) [13].

Hoogendoorn and Bovy [14] have introduced a hierarchical approach for modeling pedestrian behavior by providing three modeling levels, namely the strategic (top) level, the tactical (medium) level and the operational (low) level. An overview of these levels of behavior is given in Fig.1.8. In a pedestrian simulation engine implementing this approach, the adjacent levels interoperate by data transfer: the higher levels pass input parameters to lower levels and lower levels return processing information to higher levels.

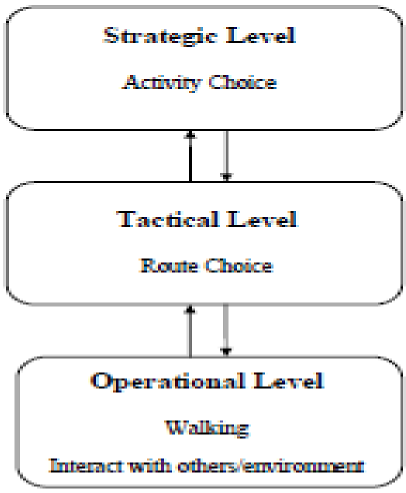


Figure 1. 8 Different levels of pedestrian behavior [14]

- ✓ ***Strategic level.*** This layer is responsible to prioritize a set of activities over another set. Pedestrians decide on the activities they intend to do.
- ✓ ***Tactical level.*** Short-term decisions are made at this level, taking into account the goals set at strategic level and based on the information about the network and existing routes and conditions. These decisions include the performance order of activities selected at strategic level and activity scheduling, activity area choice, and route choice between the origin and the intermediate or final destination of pedestrian.
- ✓ ***The operational level.*** This level describes the actual walking behavior of the pedestrians in order to avoid collision with the environment and other pedestrians.

In this hierarchy of decision making, these levels are not completely segregated from each other. Decisions made at higher levels influence choices at lower levels. Besides, expected choices at lower levels affect the decisions to be taken at higher levels.

[15] focus on pedestrian walking behavior, naturally identified by the operational level of the hierarchy just described, and are interested in modeling the short range behavior in normal conditions, as a reaction to the surrounding environment and to the presence of other individuals. It is assumed that two different categories of behaviors govern pedestrian’s walking (Fig.1.9). First category is the unconstrained behavioral pattern that refers to those pedestrian’s behaviors that are not influenced by the presence of other individuals in the environment nearby. Second one is the constrained behavioral pattern which conversely reflects the interactions between the decision-maker and other individuals in the scene.

- ✓ ***Unconstrained behaviors are:*** Toward destination, Keep direction, and Free-flow acceleration.
- ✓ ***Constrained behaviors include:*** attractive behavior of leader-follower and repulsive behavior of collision avoidance. These five behaviors are assumed to control how a pedestrian performs her walking task. Therefore, the systematic part of the utility function for each alternative is composed of the terms associated with these five behaviors and with the assumption of rational behavior, the pedestrian selects the alternative with the maximum utility.

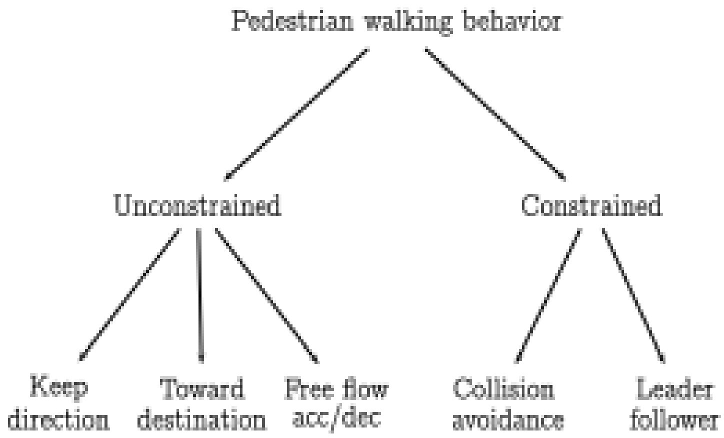


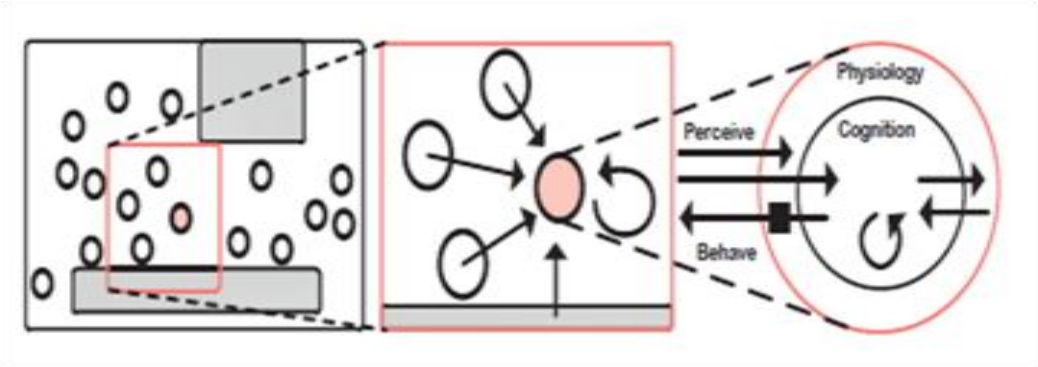
Figure 1. 9 Conceptual framework for pedestrian walking behavior [15]

Previous work has suggested that there are three levels of crowd behavior [16]: the individual, interactions among individuals and the group.

- ✓ ***The Individual.*** The behavior of crowds is derived by the individual's decision-making process which follows three basic conventions: following instinct, following experience, and bounded rationality.
  - Following instinct is the most primitive way that an individual relies on in making instantaneous and quick decisions
  - Following experience: An individual relies heavily on his/her personal experiences in making decisions. In this case, individual usually develops a set of relatively standard routines over time or from past experience and then applies them to similar situations in the future.
  - Rational decision-making assumes decisions are based on evaluation of alternatives in terms of their consequences for preferences.

- ✓ ***Interactions Between Individuals***. At this level, the social behaviors of person occur if (1) the people follow, according to their social identities, appropriate behavioral rules or procedures that they see as appropriate to the situation and with which they identify themselves, (2) individuals respect their personal spaces, and/or (3) due to a highly uncertain situation, individuals tend to follow others.
- ✓ ***The Group.*** The movement of the group (or crowd) as a singular entity is affected by both internal and external factors. Three significant factors contribute to generate group behaviors: (1) crowd density, as the density increases, individuals can be swept along with the flow of people, (2) environmental constraints which restrict the movement of the group as a whole, and perceived emotion and tension, An increase in the perceived tension in enough individuals will lead to uncoordinated movement which slows down the crowd further.

An alternative approach to describing the structure of pedestrian behavior was introduced by Wijermans [17]. The approach is called the multilevel concept and is based on crowd psychology research. It describes a link between observable group patterns, visible individual behavior, and internal cognition processes with a strong focus on the individual level, see Fig. 1.10. Three different levels are defined: the group level (inter-individual), behavior level (individual) and cognitive level (intra-individual) level. On the group level, the visible patterns of a crowd of people emerge, resulting from the subsumed individual behavior of nearby pedestrians. While this view opposes the concept of a group-mind it does not omit social concepts like leadership. On the individual level, the behavior of an individual pedestrian can be observed. The group level influences the individual behavior, e.g. by physical restrictions or social interaction. On the cognitive level, decision making is performed.



(a) The group level (b) The individual level (c) The cognitive level

Figure 1. 10 The levels at which crowd behavior can be modeled [17].

6. Virtual crowd navigation

Navigation process determines how virtual characters find and traverse paths through the environment. Once a path is defined for navigating to a specific goal, the agent must follow this path while avoiding collisions with objects in the environment and other agents. Agents should act in a realistic manner: their trajectories must be short and smooth, there should not be any collisions between agents, and the agents are typically expected to mimic human behavior. The literature covers many studies regarding the navigation of virtual characters in synthetic environments. Some of the outstanding works are summarized as follows.

6.1.Graph-Based navigation

Graph-based techniques proposed to steer characters through virtual environments, they represent the environment using a set of one-dimensional edges. Dijkstra and A* graph search algorithms can then be applied to compute the shortest path in the visibility graph.

Pettré et al. [18] proposed a method to plan and simulate the navigation of a large number of moving entities evolving on the terrain of a given virtual environment. From the environment geometry analysis, they captured its topology in a Navigation Graph structure which decomposes an environment of any kind in sets of interconnected navigable areas. Navigable areas (graph vertices) are modeled as cylinders with a variable radius. It is possible to go from an area to another one when the corresponding cylinders overlap: a vertical gate (graph edge), at the cylinders intersection, models this connection.

Geraerts et al. [19] propose a novel approach under the name corridor map method (CMM) for path planning in interactive virtual environments. The CMM consists of an off-line construction phase and an on-line query phase. In a preprocessing phase a roadmap of paths is computed for the static part of the environment. Often the medial axis is used for this. With the roadmap, clearance information is stored, defining collision-free corridors around the roadmap edges. In the query phase, when a character has to plan a path to a specific goal location, a backbone path is extracted from the roadmap together with a collision-free corridor around it. In particular, an attraction point moves along the backbone path and attracts the character in such a way that no collisions occur with the environment.

Later, I. Karamouzas et al. [20] improved the CMM algorithm and proposed an indicative routes method (IRM) to plan in real time natural paths for a large number of characters in homogeneous environments. In IRM, an indicative route determines a rough estimation of the preferred path from a character's start position to a goal position. Such a route can be manually designed or automatically computed by using, for example, an A* algorithm on a coarse grid. Then, a force-field approach guides the character through an obstacle-free area (corridor) around this route, leading to a smooth path. The IRM has been successfully used to steer in real-time thousands of characters through complex virtual worlds. However, this algorithm is only investigated analytic properties of distance propagating.

The successor of IRM, called Modified Indicative Routes and Navigation (MIRAN) [21], adopts the concept of computing an attraction point on a given an indicative route making an agent approach its attraction point based on steering forces. In each simulation step, a character chooses its best attraction point from a set of candidate points according to a weight-function that takes region preferences into account.

Jur van den Berg [22] proposed a technique that handles the navigation of multiple agents in the presence of dynamic obstacles by using a randomly sampled roadmap in order to provide path planning for the agents. For collision avoidance, He uses an extended velocity obstacles concept to locally control the agents with few oscillation.

In [23], the authors proposed an efficient method for real time path planning and navigation of multiple virtual agent based on a new date structure called "multi-agent navigation graph" or MaNG. MaNG efficiently computes dynamic navigation graphs using the first and second-order Voronoi diagrams of all the obstacles and agents present in the environment, and provides a path of maximal clearance for each agent. In order to follow the path generated using MaNG, the local dynamics of pedestrians are modeled using the generalized force model of pedestrian dynamics proposed by Helbing et al.[24]. This approach is limited to a few hundred of agents and cannot guarantee smooth motions.

Guy et al. [25] presented PLEdestrians, an optimization-based method to generate energy-efficient trajectories for each individual in a multi-agent simulation. Their model is based on a biomechanical formulation of the well-known Principle of Least Effort to guide agents along the shortest available route to the destination while simultaneously avoiding congestion, reducing the amount of movement and maintaining the underlying preferred speed for each agent. The resulting algorithm takes this function into account and computes an appropriate collision-free motion for each agent that computes a path towards the goal.

6.2. Potential Fields

The approach of potential fields generates a global field for the entire landscape where the potential gradient is contingent upon the presence of obstacles and distance to goal. These methods suffer from local minima where the agents can get stuck and never reach the goal. Since a change in target or environment requires significant re-computation, these navigation methods are generally confined to systems with non-changing goals and static environments.

The work of Jin et al. [26] allows the user to sketch velocities on anchor points in the virtual world and then uses an RBF (radial basis function) interpolation scheme to compute a continuous vector field that that directs the movements of virtual crowds. Since the field is continuous, performance is dependent on the number of anchor points rather than the size of the environment and has been shown to degrade well with increasing pedestrian sizes. The author does not however, discuss how it well it would apply to more complex environments and goal based situations.

Sachin Patil et al. [27] proposed an intuitive approach to steer and interactively direct simulation of virtual crowds using goal-directed navigation field which is free of local minima and is easily combined with most current local collision-avoidance methods. This approach can resolve congestion and generate a wide variety of macroscopic behaviors. However the generated behaviors are user-specified.

Treuille et al. [28], introduced a real-time crowd model based on using a potential function to guide pedestrians towards their goal. Dynamic potential fields have been used to integrate global navigation with moving obstacles and people, efficiently solving the motion of large crowds without the need for explicit collision avoidance. The method produces smooth behavior for thousands of pedestrians in real time, and is also able to show emergent behaviors. However, it produced less believable results, because it require assumptions that prevent treating each pedestrian with individual characteristics.

In [1], The authors extended the continuum model proposed by Treuille et al.[28] to address the crowd navigation in complex environments. Large and complex environments with multi-constructions can be represented and organized before simulation by using a semantic model, where the semantic information is described with three levels: a geometric level, a semantic level, and an application level. Each level contains different maps for different purposes, and the interactions between individuals facilitate the virtual environment. Then, the density and discomfort conversion methods are used to keep plausible distance between pedestrians and obstacles when simulating a congested crowd.

R. Narain et al. [29] proposed a novel inter-agent avoidance model which decouples the computational cost of local planning from the number of agents, allowing very large-scale crowds consisting of hundreds of thousands of agents to be simulated scalable at interactive rates. The approach can be used as a local planning module in conjunction with a global planner, such as a roadmap-based algorithm or the continuum-based optimization on a coarse grid, for the simulation of large dense crowds.

[30] proposed a formally complete and low cost solution for generating realistic and natural steering behaviors for virtual humans using path-planning based on the numerical solution of boundary value problems. It used a potential field formalism that allows synthetic actors to move negotiating space, avoiding collisions, and attaining goals, while producing very individual paths.

6.3.Multi-scale Approach

In [31], Shao and Terzopoulos modeled the virtual environment as a hierarchical collection of maps. With each of these maps designed for different purpose, the combination can support accurate and efficient environmental information storage and retrieval. As far as we know, this is the only one explicit environment model used in crowd simulation but it didn't consider the special features of regions and objects in synthetic spaces.

[32], this paper proposes a new hybrid multi-scale model, which consist of two layers: a small-scale layer modeling the navigation of pedestrians to a designated destination and a large-scale layer modeling strategic navigation, i.e. choosing different (intermediate) destinations. On the large-scale layer, a visibility graphs is constructed on top of the scenarios' geometry. The navigation graph is used to generate pedestrians' paths based on a specific navigation strategy. On the small scale layer, a cellular automaton for discretization of space and time serves as the underlying grid for constructing the navigation field. Fig. 1.11 illustrates the setup of the model.

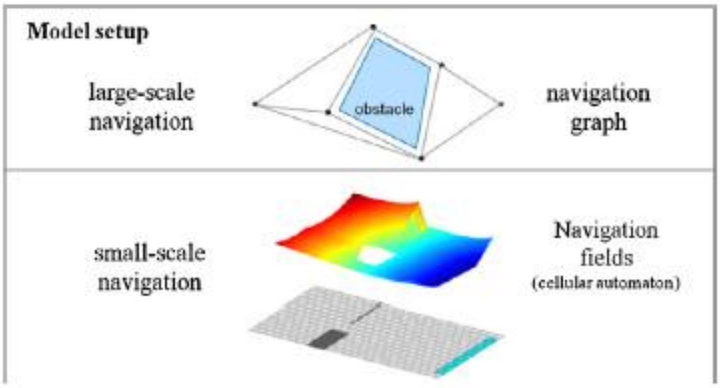


Figure 1. 11 Schematic illustration of the different implementation layers [32].

In [33], the pedestrians' routing behavior within an indoor environment is investigated with a top down approach in two levels of abstraction, i.e. both macroscopic (global) and microscopic (local) perspectives. The first stage consists to formulate an appropriate utility function that allows an effective application of dynamic programming to predict a series of consecutive waypoints with in a built environment. In the second stage, a microscopic level is adopted to deal with the pedestrian walking behavior within each segment of the path.

6.4. Hierarchical Planning.

Hierarchical planners reduce the problem complexity by pre-computing abstractions in the state space, which can be used to speed up plan efforts. Given a discrete environment representation, neighboring states are first clustered together to pre-compute abstractions for high-level graphs. Different algorithms are proposed which plan paths hierarchically by planning at the top level first, then recursively planning more detailed paths in the lower levels, using different methods to communicate information across hierarchies.

Lamarche and Donikian [34] presented a hierarchical path-planning algorithm based on sophisticated topological pre-computations. The topologic abstraction algorithm aims to generate an abstraction tree by merging interconnected cells while trying to preserve topological properties. When merging several cells into a single one, the composition of cells is stored in a graph structure in order to generate the abstraction tree. The topologic abstraction proposed by [34] relies on the topological properties of the cells and reduces the size of the graph that represents the space subdivision.

Kapadia [35] presented a real time planning framework for multi-character navigation that can efficiently work across multiple heterogeneous domains of differing complexities, by using plans in one domain to accelerate and focus searches in more complex domains. It explores different domain relationships including the use of waypoints and tunnels. The different domains use only two representations in terms of spatial subdivision, a 2D grid, and a triangular mesh. In order to showcase the ability of this framework to efficiently work across heterogeneous domains, 4 domains are described to provide a nice balance between global static navigation and fine-grained space-time control of agents in dynamic environments.

[36] proposed a new hierarchical path-finding solution for large 3D environments represented with polygonal navigation meshes. The presented solution consists of a pre-processing phase where the hierarchy is created, and an adapted version of the basic A* algorithm to perform searches online in this hierarchical representation. The off-line phase starts with a polygonal navigation mesh that represents an abstract partition of the 3D world. This first navigation mesh is considered to be the lowest level in a hierarchical tree. The rest levels of the hierarchy are recursively built by partitioning a lower level graph into a specific number of nodes. The partition is performed until the graph of the highest level cannot be further subdivided.

7. Group behaviors

In real cities, many pedestrians are part of a group, whether they are sitting, standing, or walking toward their shared goal. They behave differently than if they were alone: they adapt their pace to the other members, wait for each other, may get separated in crowded places to avoid collisions, but regroup afterwards. Several approaches have been taken in order to simulate such behaviors.

Several approaches have been taken in order to simulate such behaviors. The first approach to offer impressive results is the one of Reynolds [37], who devised intelligent rules to simulate flocks of birds and fishes.

Bayazit, Lien and Amato [38] have combined the probabilistic roadmaps approach with flocking techniques to guide the flock members toward their goals. The units use the roadmap created by PRM to guide their motion toward the goal while they use flocking to act as a group and avoid local collisions. While this indeed leads to better goal finding abilities, groups still split up easily.

Kamphuis and Overmars [39] developed a method for planning the motion of a large coherent group of units such as military armies using a multiphase algorithm. First, a path is planned for a deformable rectangle, representing the group shape. Second, the internal motion of the units inside this deformable rectangle is calculated using social potential fields. Third, the global and local paths are combined to give the total motion of the units. Although the technique guarantees coherence, it lacks completeness.

Musse and Thalmann [40] described a model to simulate group behavior based on inter-groups relationships. In their model, each group has a leader and a list of goals and goals of each member are selected from that list. Members can also change their groups in this model. This work can be seen as an early attempt to capture real-life crowd behavior with a focus on social relationships between groups and their members.

Moussaïd et al. [41] investigated the spatial organization of walking pedestrian groups in public places. He observed that at low density, people in the same group walk in a horizontal formation (line-abreast formation). While at moderate crowd density, the linear group structure will bend in the middle and form a V‘-shaped formation and finally, at high density, the group members will walk behind each other and form a "river-like" formation. Based on these observations a social-force model is proposed to model the behavior of small groups. but this method was limited by the "jitter" phenomenon of the social force model.

Based on Moussaid’s work, Karamouzas [42] adopted the velocity space to simulate the walking behavior of small groups of virtual humans, and attempted to keep the spatial arrangement of individuals in the process of interaction. The model used a two-phase approach to ensure that the group members will stay as close as possible while avoiding collisions with other groups, individuals and static obstacles. The authors suggested that this model is not designed for simulating pedestrian groups in densely packed scenarios and some collisions may occur in complex environments.

Peters and Ennis [43] proposed a model to simulate plausible behaviors of small groups in the virtual environment by analyzing the trajectory of people from the video data. Scenes were populated with different combinations of singles, pairs and groups of three and participants were asked to identify more realistic scenes. It is suggested that adding plausible groups to a pedestrian crowd scene is important for an increased sense of realism.

Qiu and Hu [44] introduced an agent-based crowd simulation framework for modeling the structural and social aspects of groups in pedestrian crowds based on social comparison theory and utility theory. In their proposed model, the dynamic grouping behavior are modeled using utility theory and social comparison theory. The dynamic grouping behavior is modeled through a two-step process. During the first step, utility theory is applied for an individual to decide which group to join (group formation). During the second step, social comparison theory is applied for an individual to decide which member of the chosen group to follow (individual selection).

Park et al. [45] proposed a pedestrian model based on the Common Ground (CG) theory to consider higher-level social interactions between the group members. It assigns a leader to each group, and it handles the task of navigation as performing a joint activity among agents, which requires effective coordination among group members. As a measure of group coherence the authors compute the distance of a follower from the leader projected on the direction of motion of the leader.

In [46], a CrowdDMX model was established, which can simulate the behavior of a subgroup among the crowd by means of psychological forces. At the same time, this model can also simulate small groups' tendency to avoid subgroup division in cases of contra-flow.

Kimmel et al. [47] presented an extension to the Velocity Obstacle (VO) approach [48] to simulate social-group behavior. The authors define a geometrical Loss of Communication Obstacle (LOCO) that can be combined with a VO to generate collision-free movement for small groups. Such groups try to stay close to each other during the simulation. Coherence is handled such that no agent is further away from the group than a particular threshold distance. There is no explicit formulation of socially-friendly formations, and the method works only locally as an extension of the VO method and its reciprocal variants, e.g. van den Berg et al. [22].

Huang et al. [49] presented a path planning method to simulate coherent and persistent groups. The method is based on the Local Clearance Triangulation by Kallmann [50], and it handles groups as deformable shapes. Deformations as well as splitting and merging actions of a group influence the overall costs of a path.

Godoy et al. [51] proposed C-Nav (short for Coordinated Navigation), an elegant distributed approach to performing implicit coordination between the local motion of the agents to improve global navigation in crowded environments. This coordination is achieved using observations of the nearby agents' motion patterns and a limited one-way communication, allowing C-Nav to scale to hundreds of agents. With this approach, C-Nav, the agents take advantage of the motion patterns of its nearby neighbors to avoid introducing constraints in their motions, and temporarily follow other agents that have similar motion. By doing this, agents in dense environments are able to reach their goals faster than using a state-of-the-art collision-avoidance framework and an adaptive learning approach for multi-agent navigation.

[52] have presented Social Groups and Navigation (SGN), a novel method that is used to simulate the walking behavior of small pedestrian groups throughout their navigation in a planar environment. SGN is based on the social force model by Moussaïd et al. [41], which we have modified and extended to generate more socially-friendly and more coherent group behavior. The generated group behavior is more flexible and diverse than with existing methods. In addition, SGN incorporates social-group behavior on the global-planning level by letting a group follow a shared global path, and by letting agents wait for each other when coherence is lost during the simulation.

8. Conclusion

In this chapter, we first qualitatively evaluate the Crowd simulation along with its key points. Studying empirical data, and simulating the behaviors, actions and movements of virtual characters in a crowd can be defined as crowd simulation. This research area has always attracted quite a significant interest from researchers of different disciplines, due to existence of large application fields such as military training, emergency planning, computer games, and architectural design.

This chapter summarizes challenging issues in crowd simulation and gives literature background regarding crowd simulation using various techniques.

Chapter 2: An Overview of Models for the Simulation of Pedestrian Dynamics

1. Introduction

From the perspective of computer graphics research, crowd simulation involves developing models and simulating the behavior of crowd and their movement to match real-world crowding scenarios. Simulations of crowd behaviors are studied in a variety of directions such as civil and safety engineering, urban and city planning, building design, and so on. In civil and safety engineering, people study the flow characteristics of pedestrian crowds in order to ensure safe evacuation under emergent situations. In urban planning and building design, pedestrian crowd simulation is used to test the reliability of public facilities and architectural designs.

Pedestrian crowd simulation also finds the application in the entertainment industry such as computer games where people study pedestrian crowd simulations to create realistic look and movement of pedestrians. The essential component which is included in pedestrian crowd simulations is the pedestrian crowd model. Over many years, people have developed many pedestrian crowd models.

In this chapter the aim will be to provide an outline of the most prominent of existing models and their classification is given. To achieve this goal, main classification of crowd simulation applications are explored in Section 2. The classification criteria are presented in Section 3. Finally, we discuss techniques used in existing crowd systems in section 4.

2. Fundamental Architectures and Classifications

Several scientists have reviewed the available pedestrian simulation models before. All reviews focus either on classifying the models according to the characteristics present within the model, the phenomena that can be simulated or the mathematical characteristics of the models. Pelechano et al. [3], and Zheng et al. [53] presented a review of crowd simulation models and discussed the advantages and disadvantages of these approaches.

Gwynne, et al. [54] summarized 22 different evacuation models in their review. Based on the nature of model application, those models are categorized into three different categories: optimization, simulation and risk assessment. Santos and Aguirre also presented a critical review of emergency evacuation simulation models [55]. They pointed out that one common shortcoming of the reviewed models lay in the absence of inclusion of social psychological relevant group level characteristics.

Zheng et al. [53] discussed the advantages and disadvantages of seven evacuation modeling techniques. Those methods include cellular automata models, lattice gas models, social force models, fluid dynamic models, agent-based models, game theory models, and approaches based on experiments with animals. The authors commented that there is a need to combine crowd modeling methods in order to improve crowd evacuation. Papadimitriou et al. [56] assess two different topics of research, namely route choice models and crossing behavior models, which study how pedestrians cross the street under different traffic conditions.

Zhou et al. [57] sort crowd models primarily based on crowd size and relevant time scales. Small-and medium-sized crowds include from a few tens up to roughly a thousand people, while a large crowd model can include tens of thousands people or more. Time scales can also vary by several orders of magnitude. Short time scale phenomena often deal with the movement patterns changing considerably within seconds or minutes. Long time scale phenomena can include social or psychological changes taking years to develop. Fig. 2.1 shows how different modeling approaches and different application categories is distributed in the two-dimensional parameter space.

Zhan et al. [58] reviewed approaches to infer crowd events by including 4 categories of crowd models from the non-vision approaches. This includes (i) physics inspired, (ii) agent-based, (iii) cellular automation and (iv) nature based. While their work acknowledged the advantages of integrating the non-vision models with computer vision methods for crowd analysis, the in-depth discussion on the different non-vision models from the physics and biology perspectives is lacking.

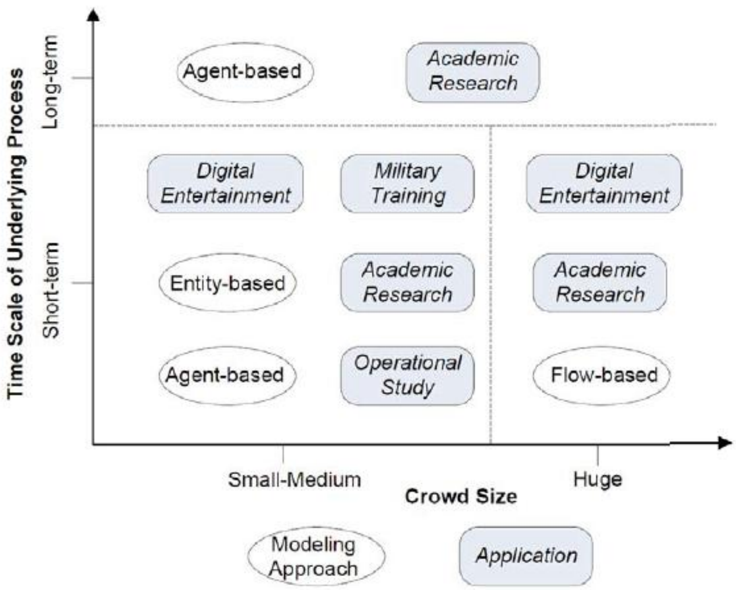


Figure 2. 1 Classification of crowd models based on crowd size and time scale [57]

Duives et al. [5] compared a number of pedestrian flow modeling approaches, focusing on how well these models are able to simulate the key phenomena indicated in the previous paragraphs. The paper discusses different types of models, such as cellular automata, social force models, velocity-based models, continuum models, hybrid models, behavioral models and network models. The comparison shows that ”the models can roughly be divided into slow but highly precise microscopic modeling attempts and very fast but behaviorally questionable macroscopic modeling attempts”.

3. Classification criteria

There are several characteristics which can be used to classify the modeling approaches:

3.1. Granularity

A basic characterization of simulation models is given by the concept of the modeled objects. In microscopic models each individual is represented separately. Such an approach allows to introduce different types of pedestrians with individual properties as well as issues like route choice. In contrast, in macroscopic models different individuals cannot be distinguished. Instead the state of the system is described by densities, usually a mass density derived from the positions of the persons and a corresponding locally averaged velocity. As a compromise in between both classes mesoscopic models have been proposed, that deal with groups of persons rather than single individuals [53].

3.2. Scale types

The most important variables for the description of the system of pedestrian are space, time and state variable (e.g. velocities), their scale types are fundamentally characterizing a model. These variables can be either discrete or continuous. In a cellular automaton approach all variables are by definition discrete whereas in hydrodynamic models all are continuous. Other combinations are used as well [57].

3.3. Determinateness

The dynamics of pedestrians can either be deterministic or stochastic. In the first case the behavior at a certain time is completely determined by the present state. In stochastic models, the behavior is controlled by certain probabilities and random variables such that the agents can react differently in the same situation [59].

3.4. Behavioral concepts

As [59] distinguishes between rule-based and force-based interaction implementations, [3] enumerates artificial-intelligence-based, functional, implicit and rule-based behavior generation and [60] states individual and collective rules to be classes of behavioral rules, in general a classification category addressing the behavioral concepts of model algorithms can be identified, with a wide range of different characteristics proposed.

3.5. Application scope

A pedestrian model is either applicable to only a certain specific problem field (typically evacuation) or it is a general model designed for a wider application area [60].

3.6. Operationalization

The application of pedestrian models happens either analytically by finding solutions of sets of equations or by simulation runs. As previously noted, this work concentrates on simulation models [60].

3.7. Fidelity level

Fidelity here refers to the apparent realism of the modeling approach. High fidelity models try to capture the complexity of decision making, actions etc. that constitute pedestrian motion in a realistic way. In contrast, in the simplest models pedestrians are represented by particles without any intelligence [60].

3.8. Behavioral level

[14] Introduce a hierarchy of three layers at which pedestrian behavior can be investigated, This criterion can be used to observe which levels are covered by a particular model:

- ✓ The strategic level addresses activity scheduling, i.e. pertains to which, in which order and where pedestrians perform activities.
- ✓ The tactical level is concerned with higher-level navigation of pedestrians in a spatial configuration, i.e. algorithms and data structures for choosing and describing paths, commonly referred to as route choice models.
- ✓ The operational level is where walking and interaction behavior of pedestrians is actually modeled.

4. Pedestrian Modeling approaches

Pedestrian behavior modeling can be classified in different ways depending upon how the scheme treats the pedestrians and the level of detail of the simulation model. Three main strategies identified for modeling of pedestrian flow are (Fig. 2.2): macroscopic; mesoscopic, and microscopic [61]. Each strategy considers a different level of abstraction. The details are as follows.

1. Microscopic models, which consider individual pedestrian behavior separately. The pedestrian behavior in these models is often described by their interactions with other pedestrians in the system.

2. Mesoscopic models, which do not consider each pedestrian individually but the overriding characteristics, such as velocity distributions. The pedestrian behavior is described microscopically though not specifically but rather in terms of velocity distributions.

3. Macroscopic models, which do not make distinctions between individual pedestrians nor describe their individual behavior but consider the flow in terms of density, average velocity and flow patterns.

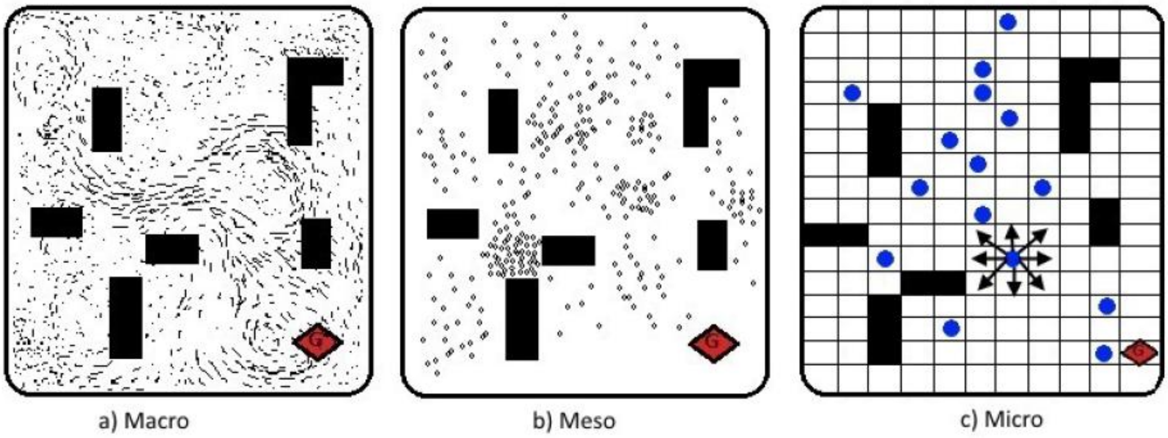


Figure 2. 2 Basic Crowd Simulation Models [61]

4.1. Microscopic Models

Microscopic models describe pedestrian flow at the level of individuals, in order to present individual behavior and interactions. The crowd are typically considered as a set of autonomous entities, which are able to follow a goal or a leader, have different attributes and intentions, and interact with each other. These models are categorized based on how they explain the relationships between the individuals.

4.1.1. Force models

Social forces models [62] assume that the movement made by each pedestrian is the result of several force terms that measure the internal motivation of the individual to perform certain actions (Fig. 2.3). Three force terms are used to describe the pedestrian motion [24]: (a) the pedestrian's acceleration to maintain his/her desired movement speed; (b) the attractiveness to activity location or to the final destination; and (c) the pedestrian's tendency to maintain a certain distance from other pedestrians and obstacles.

[63] adapt the model to better reflect evacuation and panic situations by redefining the repulsion forces of pedestrians and obstacles, and establish consistency to Newton's 2nd law of motion by considering the mass of pedestrians. The acceleration of a pedestrian i is given by

$$m_i \frac{d\vec{v}_i(t)}{dt} = \vec{f}_i^0 + \sum_{j(\neq i)} \vec{f}_{ij} + \sum_{w} \vec{f}_{iw} \qquad (2.1)$$

where m_i is the mass of pedestrian i, and $\vec{v}_i$ is the actual walking velocity. Terms on the right of Eq. (2.1) contain the desired force, $\vec{f}_i^0$, interaction forces between pedestrians i and j, $\vec{f}_{ij}$, interaction forces between pedestrians i and walls, $\vec{f}_{iw}$.

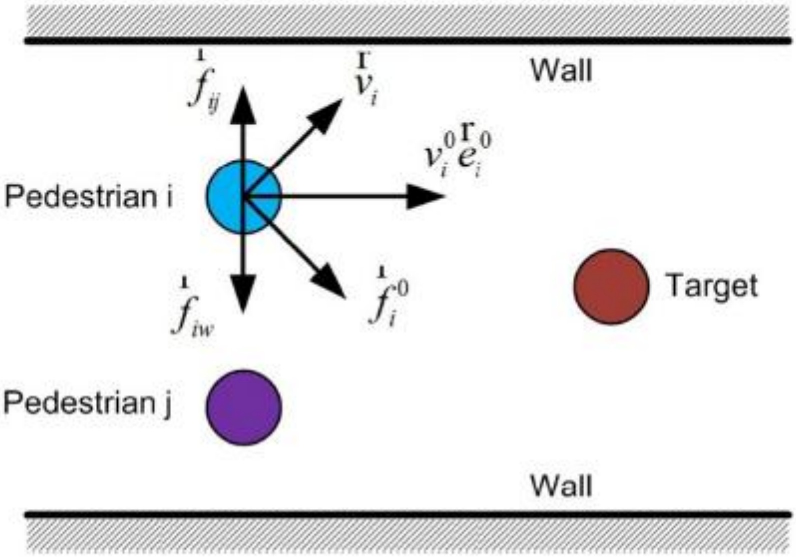


Figure 2. 3 Diagram of the social force model [62]

The interaction force between pedestrians i and j, $\vec{f}_{ij}$, mainly contains socio-psychological force, $\vec{f}_{ij}^s$, and physical force, $\vec{f}_{ij}^p$. The psychological tendency between pedestrians i and j to stay away from each other is expressed by the repulsive interaction force, $\vec{f}_{ij}^s$. The physical force exerts on people when the distance between two pedestrian centers, d_{ij}, is less than the sum of the radii of these two pedestrians, $r_{ij} = r_i + r_j$.

$$\vec{f}_{ij} = \vec{f}_{ij}^s + \vec{f}_{ij}^p \qquad (2.2)$$

where

$$\vec{f}_{ij}^s = A_i \exp\left[\left(r_{ij} - d_{ij}\right)/B_i\right]\vec{n}_{ij} \qquad (2.3)$$

$$\vec{f}_{ij}^p = kg\left(r_{ij} - d_{ij}\right)\vec{n}_{ij} + \kappa g\left(r_{ij} - d_{ij}\right)\Delta v_{ji}^t \vec{t}_{ij} \qquad (2.4)$$

Here, A_i, B_i, k, κ are constant parameters. $\vec{n}_{ij} = \left(n_{ij}^1, n_{ij}^2\right) = \left(\vec{r}_i - \vec{r}_j\right)/d_{ij}$ is the unit vector pointing from pedestrian j to pedestrian i, among which $\vec{r}_i$ is the position of pedestrian i, $\vec{t}_{ij} = \left(-n_{ij}^2, n_{ij}^1\right)$ means the tangential direction, and $\Delta v_{ji}^t = \left(\vec{v}_j - \vec{v}_i\right) \cdot \vec{t}_{ij}$ means the velocity difference along the tangential direction. g(x) is a piecewise function defined by

$$g(x) = \begin{cases} 0, & \text{if } x < 0 \\ x, & \text{if } x \geq 0 \end{cases} \qquad (2.5)$$

The interaction force between pedestrian i and walls, $\vec{f}_{iw}$, is similar to Eq. (2.4) and can be given by

$$\vec{f}_{iw} = A_i \exp[(r_i - d_{iw})/B_i]\vec{n}_{iw} + kg(r_i - d_{iw})\vec{n}_{iw} + \kappa g(r_i - d_{iw})\Delta v_{wi}^t \vec{t}_{iw} \qquad (2.6)$$

Here, d_{iw} is the distance between the center of pedestrian i and the surface of walls.

The social force model has attracted great attention from researches. Based on it, many modifications are presented to improve the performance. Daniel et al.[64] found that the social force models have some limitations when describing the experimental data of pedestrian flows in normal conditions in particular the specific flow rates for different door widths. So they proposed a modification consisting of a self-stopping mechanism.

Pelechano et al. [65] simulate the agents in a continuous space with a forces model; the movement of the agents are driven by a set of attractors while the agents avoid the obstacles and the other agents in the scene. In their model, agents may have varying personalities and roles, and the communication between the agents provide information sharing about the hazards and exit routes in the building. Their work is mainly developed for indoor emergency evacuation scenarios.

Chraibi et al. [66] introduced a spatially continuous generalized centrifugal force based model for pedestrian dynamics. This model includes elliptical volume exclusion of pedestrians and also discusses the oscillation and overlapping phenomena which occurs for certain choices of forces.

[67] improved the SFM to generates collision avoidance behaviors of individuals in the crowd by summing up an intermediate range forces. These forces consist to change the motion of an individual in order to avoid an encounter with another. The implicit assumption that will be made in the sequel is that only the local (nearest neighbors) situations influence these forces. The near-neighbor search problem is solved by an efficient incremental Delaunay triangulation that is updated at every time-step.

Yuen and Lee [68] extend the social-force model to include overtaking behavior, where pedestrians with a higher desired velocity catch up with and move past pedestrians heading in the same direction with a lower desired velocity. Lee et al. [69] presented a modified social force model by adding evasive effect and following effect to investigate the lane formation phenomenon. The following effect is adjusted to those who have the same destination, while the evasive effect is adjusted to the pedestrians who have opposite destination.

4.1.2. Rule-based models

Rule-based crowd models are flexible in simulating various crowd agents through a set of carefully-designed rules. They consist of (1) interpreting the agent's environment, and (2) rules or heuristics to react to the interpreted information. This models can provide reasonable behaviors in a dynamic environment and they are relatively easy to modify the rules to produce different behaviors. On the other hand, they result in less freedom, i.e., more predictability, they are specific to a particular environment and the number of rules can increase in complex environments.

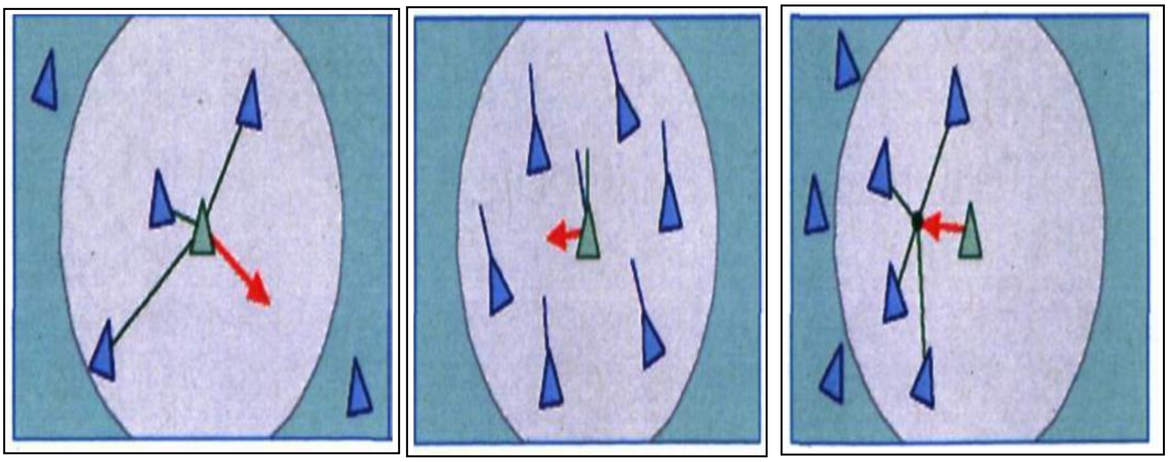
Reynolds [37] simulated flocks of bird-like entities, or boids, obtaining realistic animation by using only simple local rules as (Fig. 2.4):

- ✓ Separation: steer to avoid crowding local flockmates
- ✓ Alignment: steer toward the average heading of local flockmates
- ✓ Cohesion: steer toward the average position of local flockmates

The aggregate motion of the simulated flock is the result of the interaction of these relatively simple behaviors of the individual simulated birds.

Reynolds [70] extends the technique for flocking to include autonomous reactive behavior. The modeling of autonomous agents is performed in a hierarchical manner and specific emphasis is put on the middle layer of steering. The layers are:

- Action selection: Strategy, goals and planning,
- Steering: path determination, and
- Locomotion: Animation and articulation.



(a) Separation. (b) Alignment. (c) Cohesion.

Figure 2. 4 Rynolds's Flocks of Boids model [37]

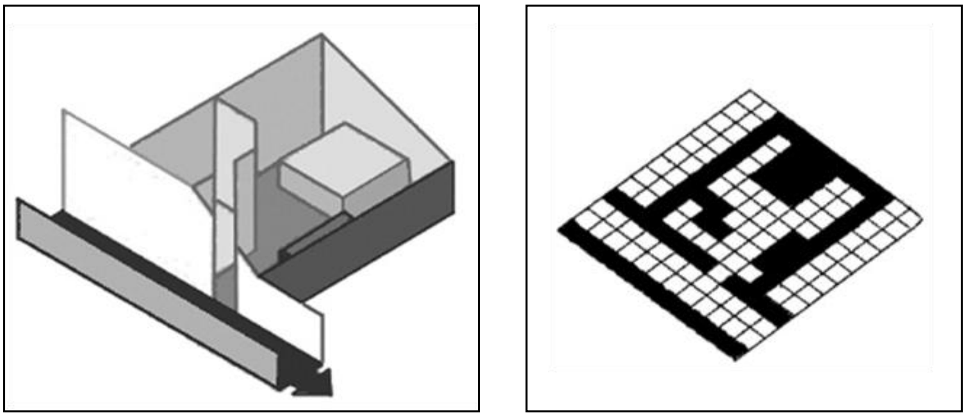
Hierarchical schemes have been proposed to address scalability. In particular, Musse et. al. [71] endow crowds with different levels of autonomy for hierarchical crowd behaviors. Depending on the level of autonomy, they employ different behavior generation techniques ranging from script-based behaviors to innate or pure reactive behaviors. However, all behaviors that they can simulate were relatively simple such as splitting, wandering, repulsing and attracting behaviors.

Similarly, Shao et. al. [12] proposed several reactive behaviors based on specific rules for controlling pedestrians. The reactive behaviors include the safety-turning, crowd direction control and collision avoidance behavior. These behaviors are processed sequentially with specific order. But, the rules for behaviors are hard to generalize to be used in other environments other than pedestrian.

4.1.3. Cellular Automata based pedestrian simulation

Cellular Automata (CA) (singular: Cellular Automaton) [3] are discrete dynamical systems that model complex behavior based on simple, local rules animating cells on a lattice. CA models have been studied in various complex systems including physics, biology and traffic modeling.

Cellular automata models divide the space in a uniform grid (Fig. 2.5). Each agent occupies a particular grid position (cell) and moves between these positions depending on the modeling system. Cellular automata evolve in discrete time steps, with the value of the variable at one cell being affected by the values of variables at the neighboring cells. The variables at each cell are updated simultaneously based on the values of the variables in their neighborhood at the previous time step and according to a set of local rules.



(a) 3D environment. (b) its corresponding grid of cells.

Figure 2. 5 Example of Cellular Automata model [3]

In general, CA provide a framework for discrete models with locally homogeneous interactions. They are characterized by the fundamental properties (L, S, N, f) shown in Table 2.1. The assumption of a regular lattice and a uniform neighborhood is compatible with geometries like those in Table 2.1 since the set of states, S, also contains information about whether a cell is accessible or not (e.g., doors or walls between cells).

Table 2.1: Definition of a cellular automaton [3]

L	**Consists of a regular discrete lattice of cells**
$t \rightarrow t + 1$	Evolution takes place in discrete time steps
S	Set of finite states
$\mathbf{F}: \mathbf{S^n} \rightarrow \mathbf{S}$	Each cell evolves according to the same rule (transition function), which depends only on the state of the cell and a finite number of neighboring cells
$\mathbf{N}: \forall \mathbf{c} \in \mathbf{N}, \forall \mathbf{r} \in \mathbf{L}: \mathbf{r} + \mathbf{c} \in \mathbf{L}$	The neighborhood relation is local and uniform

CA were originally used for vehicular simulation. Blue and Adler [72] showed that it could be extended into the more complex domain of pedestrian simulation. They describe a CA micro-simulation model which uses lane selection and speed determination to reproduce observable pedestrian phenomena in both uni-directional and bi-directional flows. In this model, pedestrians try to choose a lane which allows them to reach their maximum desired speed more freely. Simulation experiments indicate that the basic model is applicable to walkways of various lengths and widths and across different directional shares of pedestrian movements.

Daoliang et al.[73] developed a two-dimensional cellular automata model to simulate the egress dynamics during evacuation. The developed model is used to derive useful information on the required width of the exit gates and recommended gate separation.

Abdelghany et al. [74] presented a cellular automata crowd simulation model for large-scale facilities. A behavioral module in the form of a logit-based model is used to replicate how evacuees select their exit gates. The model captures the trade-off between travel distance to the gate and the level of congestion at the gate. The model is applied to study the evacuation of a crowded pilgrimage facility in Mecca, Saudi Arabia.

[75] proposed a new modeling framework that integrates a dynamic simulation-assignment logic with a hybrid (two-layer) representation of the facility. The top layer consists of a network representation of the facility, which enables modeling the pedestrians' route planning decisions while performing their activities. The bottom layer consists of a high resolution Cellular Automata (CA) system for all open spaces, which enables modeling the pedestrians' local maneuvers and movement decisions at a high level of detail.

4.1.4. Lattice gas models

The lattice gas model (LG model) is a special form of the CA model. There are two differences though. First, instead of a regular grid, LG models consider a triangular lattice with a hexagonal symmetry. Second, concept of a cell is replaced by a site which can be occupied by more than one individual. The sites on the lattice can take a certain number of different states [76]. The various states are pedestrians with certain velocities. Evolution of the simulation is done in discrete time steps. After each time step, the state at a given site can be determined by the state of the site itself and neighboring sites, before the time step.

Song et al. [77] proposed a multi-grid model that uses a lattice gas (LG) with force essentials, i.e. repulsion, friction and attraction, to study the evacuation behaviors at exit.

In the model, one pedestrian occupies multiple grids instead of only one, and overlapping of pedestrians is allowed. The model can simulate crowd evacuation more realistically. They also developed a multi-grid model [78], which discretized a cellular space into a finer lattice, to simulate evacuation with pedestrians having different moving step size. By considering the spatial and temporal characteristics, Guo et al. [79] developed a heterogeneous LG model. All these models mentioned above are based on a two-dimensional grid flow model, i.e., the evacuation space is limited to the same plane.

The paper [13] develops a model consisting of two sub-models, while the Environmental Model manages the spatial real-time environment using CA and the Pedestrian Model bases on behavior agents to respond to the real-time environment. The model can simulate a set of individuals with heterogeneous behaviors.

4.1.5. Floor field

The floor field model, which is a type of CA model, is able to describe many of the remarkable collective behaviors of pedestrian dynamics. The floor field helps all pedestrians to move in a certain geometry to the destination [80].

In general, there are two types of floor fields: the static floor field S and the dynamic floor field D [81]. The static field depends only on the distance measure (from a cell to the destination), and thus S remains unchanged in the evolution. The dynamic field reflects the virtual tracks left by moving pedestrians. On the one hand, the cell (x, y) that a pedestrian leaves becomes empty and attractive, with $D_{xy} \rightarrow D_{xy} + 1$. On the other hand, D_{xy} decays and diffuses with certain probabilities (δ and α) so that the cell will not become too attractive to induce too many conflicts or too high densities in the surroundings.

Suma et al. [82] proposed anticipation floor field (AFF) to extend floor field models. The anticipation behavior is ‘‘the ability of avoiding collisions with other pedestrians considering their future walking way’’ in this paper. Then, the anticipation is divided into two steps:

a) recognizing the area that is expected to be occupied by the other pedestrians in the future,
b) changing direction or speeding down/up the walking speed referring to the area obtained in the step (a) to avoid collisions.

The cost potential field is extended to simulate pedestrian flow in a walking facility with complex geometries, in which visibility is considered [83]. To reflect the influence of visibility on the path-choice strategy, a perceived cost potential field is constructed by taking a memory potential. The memory potential is measured by the distance from the cell to the destination, which is actually a degenerated cost potential, such that the surroundings are completely invisible and pedestrians are only able to conceive of the path to their destination according to their experience.

An improved floor-field CA pedestrian model are proposed by Bandini et al. [84] to investigate the simulation of high density situations comprising negative interactions among pedestrians. In this model, path fields, the obstacles field, and the density field are adopted to describe the pedestrian behaviors. In addition to the basic model, two extensions were introduced: a model allowing transient pedestrians overlapping in high density situations and a model characterized by a finer discretisation of the environment.

4.1.6. Agent-Based models

Agent-Based Modeling (ABM) is a computational simulation methodology used to build an artificial society, and considered as one of the most realistic among existing egress simulation techniques [16]. In such model, pedestrians are represented by computer-driven entities (agents) that have heterogeneous characteristics and are adaptive. Agents are autonomous units, capable of interacting with surrounding entities, the environment and other agents and able to make independent decisions. The interactions of interdependent agents generate complex systems, potentially leading to emergent behavior at the system level.

Shendarkar et al. [5] proposed to use an extended BDI (Belief-Desire-Intention) framework to realistically model the human behaviors in crowd simulation. To this end, the intention module in the traditional BDI is expanded to include detailed sub-modules such as 1) deliberator, 2) real-time planner, and 3) decision executor in the decision-making. This extension was necessary to accommodate both the decision-making and decision- planning functions in the unified framework. This extension was necessary to accommodate both the decision-making and decision- planning functions in the unified framework. In addition, emotional module containing confidence index and instinct index has been also appended to represent more psychological human natures.

While this work [85] focused only on the conceptual extension of the BDI model, Lee and Son [86] attempted to build a comprehensive model for human decision behavior (which includes decision making and decision planning), integrating aspects of previous models which Lee and Son categorize as engineering, psychological, and economical. Their model used Bayesian belief networks, decision field theory, and probabilistic depth first search. Their extensions to the BDI framework showed promising results of simulated human behavior in dynamic and intricate situations.

Pan et al. [16] developed a computational framework, Multi-Agent Simulation System for Egress analysis (MASSEgress), which is capable of modeling human and social behavior during emergency situations. In this model, human cognitive processes are simulated by a ‘‘perception-action’’ model, in which an agent continuously assesses or ‘‘senses’’ the surrounding environment and makes decisions based on its decision model in a proactive fashion.

An upgraded version of MASSEgress, SAFEgress (Social Agent For Egress simulation), is developed by Chu et al. [87], in which occupants behaviors are modeled through a five-stage process (perception, interpretation, decision-making, execution, and memorization). The pedestrian behaviors are comprised of individual behavioral models, group behavioral models, and crowd behavioral models. Results from the SAFEgress prototype show the production of three group behaviors including leader-following, group-member-following, and group-member-seeking responses. Similar to MASSEgress, environmental hazards are not accounted for. In addition, the group behavior models need to be refined to account for the type of gathering and social relations such as kinship, friendship, etc.

Koh et al. [88] developed an agent-based model for crowd simulation. Their focus was to produce a two-tiered model capable of producing realistic agent navigation and path-planning within the environment whilst maintaining real time frame rates. The macro level governed the path coordination, while the micro level handled sub-goals such as avoiding other agents. Agents were endowed with the ability to remember a map, have limited range of vision, and have a limited memory of events such as encountering obstructions. Simulations demonstrated following, overtaking, and congestion avoidance behaviors.

Luo et al. [89] adopt an agent-based approach and employ a layered architecture to reflects the natural human-like decision-making and behavior execution process which generally involves a person's awareness of the external situations and consequent changes on the internal attributes. The person's awareness of the current situation is based on the existing expectations about people, social roles, and events, and is triggered by some external stimulus (the sensory inputs). The consequent changes on internal attributes delineate a person’s internal feelings, social states, as well as physical conditions. The decision making will be directly affected by these internal attributes and people can make different decisions under the same situation due to the different levels of variations on their internal attributes.

In [90], a novel pedestrian flow simulation model, namely, CityFlow is developed to naturally reproduce pedestrian behaviors for different environments. In CityFlow, pedestrian behaviors are implemented d by two modules at three levels: (1) the route choice and map navigation module identifies the temporary desired regional target of movement, reflecting strategic, tactical level behavior in macroscopic scope; (2) the agent-based individual movement module uses a utility maximization approach to calculate the movement direction of the agents based on detailed environmental information at every time step, reflecting operational level behavior in microscopic scope.

CityFlow was proved to be a flexible platform for pedestrian flow simulation in metro stations, with natural consideration of various observed pedestrian behaviors inside metro stations such as queuing and waiting behaviors [91].

In CityFlow-U [92], which is an expanded version of CityFlow, a new module named (3) the attention-based exploratory movement module has been added. This module enables the agent to explore the visual attractors and then decide whether it will be distracted from the pre-defined routes by examining attractor characteristics and agent’s internal state of demand.

4.2. Macroscopic models

The focus of the macroscopic models is on the crowd as a whole especially in high density situations, pedestrians are not represented individually. Macroscopic-based approaches aim to realistically simulate global crowd phenomena such as the formation of lanes when two groups cross ways, giving less emphasis to local phenomena such as collision-avoidance between two pedestrians [93].

Accordingly, the state of the crowd is described with aggregate observables, such as density and velocity, and the dynamics is governed by two partial differential equations (PDEs), expressing the conservation of mass, momentum and energy [94].

$$\begin{cases} \partial_t \rho + \nabla_x(\rho v) = 0 \\ \partial_t v + v \cdot \nabla_x(v) = A[\rho, v] \end{cases} \tag{2.7}$$

Here, $v = v(x, t)$ is the dimensionless velocity, $x = (x, y)$ represents coordinates, $A[\rho, v]$ models the component of the mean acceleration, acting on pedestrians. The square brackets indicate that it may be a functional of its arguments.

According to the specific constitutive assumption, different models can be derived that involve only some of the three equations in (2.7). They can be classified as follows [95]:

- ✓ Scalar or first order models: They are described by mass conservation equation only, and by a closure equation $v = v[\rho]$ that links the local velocity to the crowd density [96] [93].
- ✓ Second order models: They are obtained by mass and linear momentum conservation equations with the addition of a phenomenological relation describing the psycho-mechanic action $A[\rho, v]$ on the pedestrians [97].

4.2.1. Hughes Model

[98] developed a first-order model describing the motion of large, goal-directed crowds. The basic relationship of the two central variables of pedestrian flow, i.e., density and velocity, is given by the flow conservation

$$\frac{\partial \rho(x, y, t)}{\partial t} + \nabla \cdot \big(\rho(x, y, t) v(x, y, t)\big) = 0 \tag{2.8}$$

where ρ is the pedestrian density and $v = (v_1, v_2)$ is the pedestrian flow velocity, each at location (x, y) and time t.

Hughes defined a potential function $\phi(x, y, t)$ and proposed that the motion of any pedestrian is in the direction to this potential, that is, in the direction for which

$$\widehat{\phi}_1 = \frac{-\phi_x}{\sqrt{\phi_x^2 + \phi_y^2}}, \quad \widehat{\phi}_2 = \frac{-\phi_y}{\sqrt{\phi_x^2 + \phi_y^2}} \tag{2.9}$$

Therefore,

$$v_1(x,y,t) = u(x,y,t)\hat{\phi}_1(x,y,t), \qquad v_2(x,y,t) = u(x,y,t)\hat{\phi}_2(x,y,t) \quad (2.10)$$

where $u(x,y,t)$ is the pedestrian speed which is a function of density and is location dependent, i.e.,

$$u(x,y,t) = U\big(\rho(x,y,t)\big) \qquad (2.11)$$

To account for the discomfort effect, Hughes defines a function

$$g(x,y,t) = G(x,y,t) \qquad (2.12)$$

that describes the behavior of a pedestrian to avoid high density crowds, which satisfies the following equation:

$$\frac{1}{\sqrt{\phi_1^2 + \phi_2^2}} = g(x,y,t)\|v(x,y,t)\| = g(x,y,t)u(x,y,t) \qquad (2.13)$$

Hughes [98] provided a systematic framework for the dynamic macroscopic modeling of pedestrian flow problems based on three hypotheses: (i) pedestrians' speed is determined by the local density at their location (Eq. (2.11)), (ii) pedestrians' movement is perpendicular to lines of constant potential (Eq. (2.10)), and (iii) pedestrians want to take the path with the shortest travel time, but only if the density on this path is not too high (Eq. (2.13)). However, the physical interpretation of the potential field and the route strategy of pedestrians in a crowd are not explicitly revealed in this model.

4.2.2. Reactive dynamic user equilibrium model

The reactive dynamic user equilibrium model describes the movement of pedestrians who do not have predictive information when they are making a path-choice decision [95, 99]. This means that pedestrians have to rely on the instantaneous information available to them and make their choices in a reactive manner to minimize the walking cost to their destination.

In [99], a pedestrian flow model based on the reactive dynamic user equilibrium principle is developed, where pedestrian density is governed by the scalar two-dimensional conservation law and the flow flux is implicitly dependent on the speed through an Eikonal equation.

Along the direction of the flow vector (or movement), flow intensity, which is determined as the norm of the pedestrian flow, is equal to the product of speed and density,

$$\|\mathrm{f}(\mathrm{x},\mathrm{y},\mathrm{t})\| = \mathrm{u}(\mathrm{x},\mathrm{y},\mathrm{t})\rho(\mathrm{x},\mathrm{y},\mathrm{t}) \qquad (2.14)$$

A cost potential function $\phi(\mathrm{x},\mathrm{y},\mathrm{t})$ is defined which satisfies the Eikonal equation:

$$\|\nabla\phi(\mathrm{x},\mathrm{y},\mathrm{t})\| = \mathrm{c}(\mathrm{x},\mathrm{y},\mathrm{t}) \qquad (2.15)$$

where $\mathrm{c}(\mathrm{x},\mathrm{y},\mathrm{t})$ is the local cost that is related on walking speed alone and can be specified as

$$\mathrm{c}(\mathrm{x},\mathrm{y},\mathrm{t}) = \frac{1}{\mathrm{u}(\mathrm{x},\mathrm{y},\mathrm{t})} \qquad (2.16)$$

To ensure the reactive user equilibrium condition in which pedestrians choose a path that minimizes their total cost to a destination according to instantaneous pedestrian flow information, the following equation must be defined

$$\mathrm{c}(\mathrm{x},\mathrm{y},\mathrm{t})\frac{\mathrm{f}(\mathrm{x},\mathrm{y},\mathrm{t})}{\|\mathrm{f}(\mathrm{x},\mathrm{y},\mathrm{t})\|} + \nabla\phi(\mathrm{x},\mathrm{y},\mathrm{t}) = 0 \qquad (2.17)$$

In [100], another efficient method, the discontinuous Galerkin (DG) method for the conservation law coupled with the fast sweeping method for the Eikonal equation, which works nicely on triangular meshes, has been developed for the model.

Xia et al. [101] introduced a model with memory effect, in which pedestrians aim at following the shortest path to the destination based on the memory of its location, and temper their behavior locally to avoid high densities.

Jiang et al. [102] extended the reactive dynamic continuum-user equilibrium model to simulate bidirectional pedestrian flows that can be used to simulate two groups of pedestrians traveling on crossing paths. The emergence of lanes and strips is reported. In addition, [103] proposed a high-order computational scheme for the Jiang et al. [102] model, which proved to be more efficient than the first-order method.

4.2.3. Gas Dynamics Approach

This approach is presented by Bellomo and Dogbe [104]. Consider the crowd in a bounded domain $\Omega \in \mathrm{IR}^2$ where $\partial\Omega$ is its boundary. The overall description of the system is delivered by the equation of conservation of mass and equilibrium of linear momentum defined by the following system of partial differential equations:

$$\begin{cases} \partial_t\rho + \nabla_x \cdot (\rho u) = 0 \\ \partial_t u + (u \cdot \nabla_x)u = F(\rho, u) \end{cases} \qquad (2.18)$$

where F models the average acceleration that acts over the elementary block of individuals in volume $dxdy$. Bellomo et al presented three different classes for various F.

Class one refers to systems where the pedestrians move along straight lines towards the target objective.

$$\begin{cases} \partial_t \rho + \nabla_x \cdot (\rho u) = 0 \\ \partial_t u + (u \cdot \nabla_x) u = \alpha(U(\rho) e_0 - u) - \dfrac{K^2(\rho)}{\rho} \nabla_{e_0} \rho \end{cases} \qquad (2.19)$$

where $\alpha > 0$ is the inverse of the relaxation time, e_0 is a unit vector pointing towards the target and $U(\rho)$ is an equilibrium speed of pedestrians. The second class of models refers to walkers that still move towards the target objective, but are also attracted by paths with small density gradients.

$$\begin{cases} \partial_t \rho + \nabla_x \cdot (\rho u) = 0 \\ \partial_t u + (u \cdot \nabla_x) u = \alpha(U(\rho) e - u) - \dfrac{K^2(\rho)}{\rho} \nabla_{e} \rho \end{cases} \qquad (2.20)$$

where direction of motion is given by $e = e_0 + e_1$, with e_1 being the correction term related to the attraction towards small density gradients.

The third class of models contains a pressure term which enables the momentum equation to predict the expected response of crowd behavior as time and space changes.

$$\begin{cases} \partial_t \rho + \nabla_x \cdot (\rho u) = 0 \\ \partial_t (u + P(\rho, u) u_0) + (u \cdot \nabla_x)(u + P(\rho, u) u_0) = \alpha(U(\rho) e_0 - u) \rho \end{cases} \qquad (2.21)$$

where $P = P(\rho, u)$ is some pressure that pedestrians feel along the preferred path, depending on pointwise crowding of the domain and on their current velocity.

4.2.4. Second-order model

Jiang et al. [97] described a higher-order macroscopic model for unidirectional pedestrian flow. The model derives from fluid dynamics and consists of mass and momentum balance equations with source term. The model reads

$$\begin{cases} \dfrac{\partial \rho}{\partial t} + \nabla \cdot (\rho v) = 0 \\ \dfrac{\partial v}{\partial x} + (v \cdot \nabla) v + c^2(\rho) \dfrac{\nabla \rho}{\rho} = \dfrac{U_e(\rho) \vec{\mu} - v}{\tau} \end{cases} \qquad (2.22)$$

where $\rho(x, y, t)$ denotes the density of the unidirectional pedestrian flow; $u(x, y, t)$, $v(x, y, t)$ are the average speeds of pedestrian motion in the x- and y-direction, $c^2(\rho)\frac{\nabla\rho}{\rho}$ describes the anticipation term, which reflects pedestrian reaction to the surrounding pedestrians, $\frac{U_e(\rho)\vec{\mu}-v}{\tau}$ is a relaxation term towards a desired velocity.

The unit vector $\vec{\mu}$ describes the desired direction of motion, it is tangential to the gradient of $-\phi$, and is given by

$$\vec{\mu} = -\frac{\nabla\phi(x, y, t)}{\|\nabla\phi(x, y, t)\|} \qquad (2.23)$$

The potential ϕ corresponds to an instantaneous travel cost which pedestrians want to minimize and is determined by the eikonal equation

$$\begin{cases} \|\nabla\phi\| = C(x, y, t) & \text{at any point } (x, y) \\ \phi = 0 & \text{on the goal} \end{cases} \qquad (2.24)$$

$C(x, y, t)$ is the local travel cost distribution, which is defined as

$$C(x, y, t) = \frac{1}{U_e(\rho)} + g(x, y, t) \qquad (2.25)$$

where the dominant term $\frac{1}{U_e(\rho)}$ is the time cost distribution and the trivial term $g(x, y, t)$ is related to a discomfort field.

The equations (2.22)-(2.25) constitute a higher-order macroscopic model for unidirectional pedestrian flow. This model is extended to describe macroscopic features and path choice behaviors of bi-direction pedestrian flow [105].

The two equations (2.23) and (2.24) can guarantee pedestrians tend to walk along a path with the lowest instantaneous cost. However, the desired direction of motion in this model is fixed at any point of the facility and does not change with the time-varying traffic conditions. Therefore, it can’t quite express the real path-choice behavior of pedestrians.

For the issue mentioned above, in [106] a second-order predictive dynamic model for pedestrian flow is presented to describe that pedestrians are inclined to choose a path with the lowest actual cost based on predictive traffic information.

4.3. Hybrid models

Recently, researchers investigated the hybrid approaches by combining both macroscopic and microscopic techniques that complement each other. Existing work has attempted to use both types of models either partially or completely [107, 108]. These recent developments in hybrid models can be considered in following two categories [61, 109]:

4.3.1. Zone Based Models

In this approach, simulation space is divided into multiple zones. Based on application needs, each zone is simulated either for macroscopic or microscopic model. Zone simulated under macroscopic technique provides overall flow of crowd whereas zone simulated with microscopic model offers individual level behaviors observation. Generally, the proposed techniques run both models simultaneously on pre-defined zones [108]. Usually, the macro model is used to simulate the homogenous crowd in large area where objective is to have smooth flow. In contrast, few parts are marked as decision points (road intersection, doors etc) to observe the behaviors of individuals.

Anh et al. [110] proposed a hybrid approach that combines a macro and micro models to simulate the pedestrian movements in the study of evacuation problem on a road network. They use an agent based Leader-Follower approach to simulate the pedestrian behaviors in the cross-section (where a decision must be taken), and the movements in the straight parts of the streets are calculated by the LWR-model.

Yersin et al. [108] present a hybrid approach for real time crowd motion planning. A navigation graph is used to divide the environment into zones of varying interest. The potential fields are used only for those parts of a navigation graph that lie in a high interest region. In the other regions, the pedestrian behaviors are ruled by the navigation graph and a short term avoidance algorithm.

A hybrid modeling method is proposed to simulate the evacuation scenarios and the normal flow of crowd in [111]. Authors combined macroscopic and microscopic models in a single simulation and executed them simultaneously by applying them to multiple partitions of a corridor. Individuals in crowd need a smooth transition between the two different zones known as aggregation and disaggregation as shown in Fig. 2.6. However, this approach restricts the possible movement direction of crowd which makes it less suitable for simulating large social events and gatherings in open space [112]. Moreover, global and individual features of simulation could not be observed simultaneously in same zone.

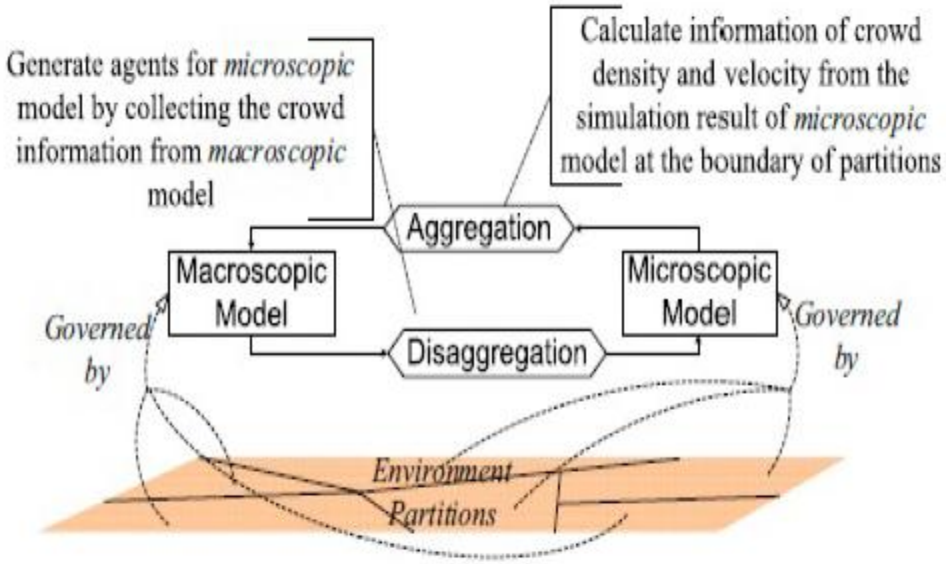


Figure 2. 6. Deployment of Zones based Hybrid Model, [111].

On the contrary, dynamic coupling of macro and micro approach in desired zone to simulate large scale traffic flow has been proposed in [113]. This enabled automatic switching between two simulation models based on certain criteria (application requirement, volume and velocity of traffic, desired behaviors etc). It gives freedom to observe simulation as per user desire under macro model for overall flow of traffic or to simulate heterogeneous individual cars by a micro model.

4.3.2. Sequential Models

Similar to layer based hybrid models, another approach is sequential hybrid technique which also runs both macro and micro models for whole crowd [109]. However, it first runs macro model to guide the movement pattern of crowd and then applies micro model to same crowd for observing the individual behaviors.

It executes both models in sequential manner where a synchronization method is required to transfer the crowd state between both modes. Initially, macro model runs based on speed-density relationship to simulate the crowd movement. Within same simulation time step, synchronization module helps to transfer macro results to microscopic model. Later, microscopic model is executed based on movement pattern and density generated in first macro step. Hence, synchronization mechanism is critical to transfer results of both simulations models within one time step between each another.

5. Conclusion

This chapter has reviewed the theoretical backgrounds and existing methods for pedestrian behavior modeling. A critical discussion is provided to clarify the benefits and limitations of different approaches.

According to the literature survey presented in this chapter, classic macroscopic, mesoscopic and microscopic models alone cannot provide user desired functionality in an efficient manner. In the last section, we provide an overview of existing hybrid techniques in crowd simulation and modeling. We classify and discuss these models as zone based, layered and sequential hybrid models based on their functionality related to physical space.

Chapter 3: Motion Planning and Navigational Behaviors in Virtual Environments

1. Introduction

The navigational behaviors of a pedestrian crowd refer to how the pedestrians move to reach their destinations in a complex and dynamic environment with static obstacles and moving objects. Solving this problem requires several advanced features such as visually convincing and smooth trajectories, clearance from obstacles, collision avoidance between characters. Viewed from this perspective, generating navigation behaviors is still a challenging task for computer programs to imitate such behaviors realistically. Depending on the scale of the environment, complex navigational behaviors are generally charger with two different activities: path planning and a collision avoidance algorithm.

Path planning can be considered to be the higher-level cognitive activities that generate a global route directing the agent from its current position to the goal. It typically considers the static aspects of the environment, such as walls and doorways in the relatively long term in both spatial and temporal domains. If we had a map of the environment, this would be relatively easy. Collision avoidance is very important. Every pedestrian should avoid each other. It is not acceptable to have the pedestrian walk straight through the obstacles. These models enable users to investigate interactions of individuals in a crowd to the building details, emergencies, crowd density, and actions of other pedestrians.

The purpose of this chapter is to provide a detailed discussion of navigation behaviors required in virtual crowd simulation system. In section 1, we will discuss the popular spatial partitioning data structures. We review path-planning techniques algorithms for efficiently computing paths in dynamically changing environments. An overview of general collision avoidance algorithms is given in section 3.

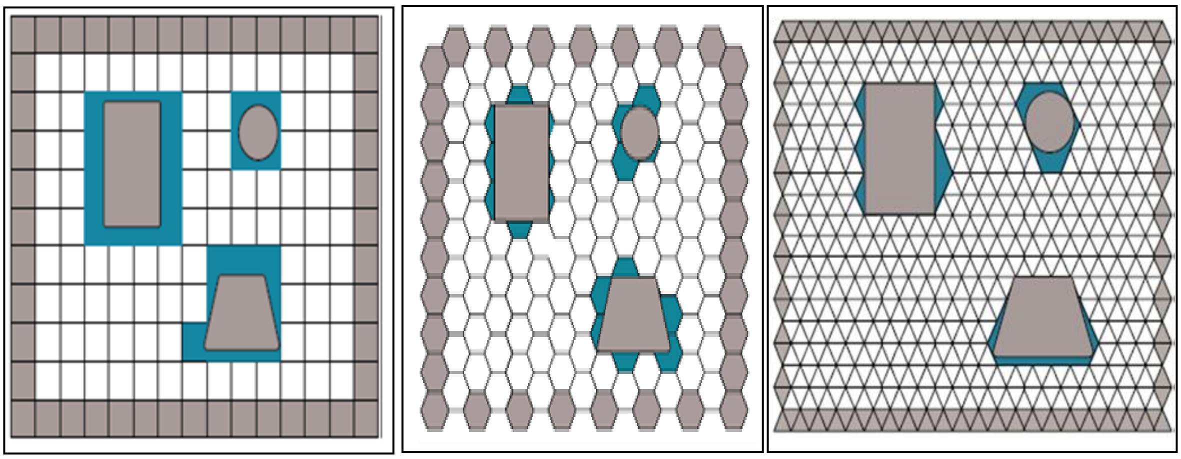
2. Representing traversable space in virtual worlds

The representation of the walkable area of a 3D environment in such a way as to facilitate successful navigation by intelligent agents is an important problem in the computer games and artificial intelligence fields, and it has been extensively studied. We provide a broad overview below and refer the readers to [114] for additional details. There are a variety of common ways to represent such an environment, including:

- ✓ Regular Grids. These consist of decomposing free spaces into regular cells. Once this decomposition is computed, a connectivity graph can be extracted, whose nodes are cells and edges traduce cells adjacency.
- ✓ Waypoint Graphs. These connect large numbers of nodes (often manually placed) using edges that imply walkability in the game world. They were previously popular in games but are costly to build and tend to constrain agents to walking `on rails' between connected waypoints.
- ✓ Navigation Meshes. These represent the walkable surface of a world explicitly using a polygonal mesh. Polygons within a navigation mesh are connected using links that imply the ability of the agent to walk/step/jump/etc. between them.

2.1.Grid-based approach

Grids constitute the most straightforward way to represent the traversable space of an environment for path planning [115]. The most common types are rectangular or square grids. However, other types have been widely used in simulations and games, too. The basic idea consists of the partition of the navigable geometry of the scene into cells of a particular shape and with a particular grid resolution. Each cell can have two states: free, partially obstructed, and totally obstructed or obstacle [116]. Hexagons, squares, and triangles are the only regular polygons that can be used to tessellate continuous 2D environments (Figures 3.1 (a)–3.1(c)) and 3D cubic grids [117].



(a) square grid (b) hexagonal grid (c) Triangulation grid

Figure 3. 1 Regular Grid decomposition [117]

Hexagonal grids are common, as well as grids with isometric diamond-shaped tiles; see Fig. 3.1. From a topological point of view, isometric grids and rectilinear grids are equal. They are commonly used in 2D games to simulate an isometric view on pseudo-three-dimensional game worlds in which correct clipping is easily achieved by rendering objects on the grid from top to bottom along the screen.

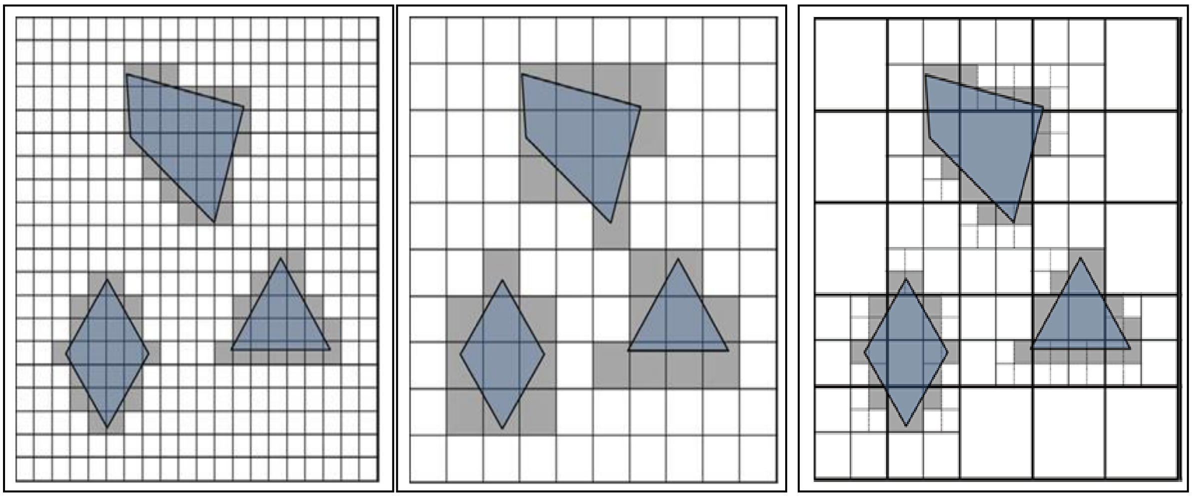
Rectangular grids are also used in many traditional and modern board games, and have also been widely used in pen and paper role-playing games to simulate combat scenarios. 2D Hexagonal Grid (Fig. 3.1(b)) have many of the desirable properties of square grids. In addition, hexagonal grids have smaller search time and memory complexities than grid graphs constructed from squares. Hexagonal grids become triangular and vice versa, see Fig. 3.1. Thus, using the center points of hexagonal cells as possible character positions is technically the same as performing path-finding on a triangular graph [116].

3D Cubic Grid. is a regular graph based on a continuous 3D environment [117].

The accuracy of the obtained representation basically depends on the cell size: the larger cells are, the less precise is the representation (see Fig. 3.2 (a)). Of course, increased precision leads to an increase in memory use (see Fig.3.2 (b)). The memory footprint of this method is thus its first weak point. It directly affects the complexity of path search in the environment. In order to reduce this problem, an extension of this model has been proposed in the form of hierarchical grids [118].

Quadtrees [114] have been proposed as a way of doing hierarchical map decomposition. This method partitions a map into square blocks with different sizes so that a block contains either only walkable cells or only blocked cells (Fig. 3.2 (c)). The problem map is initially partitioned into 4 blocks. If a block contains both obstacle cells and walkable cells, then it is further decomposed into 4 smaller blocks, and so on. An action in this abstracted framework is to travel between the centers of two adjacent blocks. Since the agent always goes to the middle of a box, this method produces sub-optimal solutions.

While grids are easy to implement, a major problem is that grids may not cover all of the traversable space that is visually displayed to the user. Some corners of the virtual world and important passages between obstacles might not be traversable due to a too coarse grid resolution;



(a) fine grid resolution (b) coarse grid resolution (c) Grid abstraction using a three levels quatree.

Figure 3. 2 Approximative decomposition by grids [117]

2.2.Roadmap approach

The roadmap approach consists of computing a network of standardized paths (lines, curves) passing through free space. Once the roadmap has been constructed, a path can be calculated by connecting the initial and final positions in the network and finding a path in the roadmap (Fig.3.3). Probabilistic Roadmaps, Visibility Graphs and Generalized Voronoi Diagarams are examples of roadmap methods.

The main limitation of this representation is that it only contains information about which locations of the scene are directly connected, but it does not describe the geometry of the scene, nor where the obstacles are. Consequently, avoidance of dynamic obstacles is usually a hard task and not always possible [114].

2.2.1. Probabilistic Roadmap Method (PRM)

The probabilistic roadmap [119] is one of the frequently used techniques nowadays. This method consists of two phases. In the construction phase, a roadmap is created by generating a set of randomly distributed way points and linking them together with collision-free paths. In the query phase, the start and goal positions are connected to the graph, and the path is obtained by running Dijkstra's shortest path algorithm.

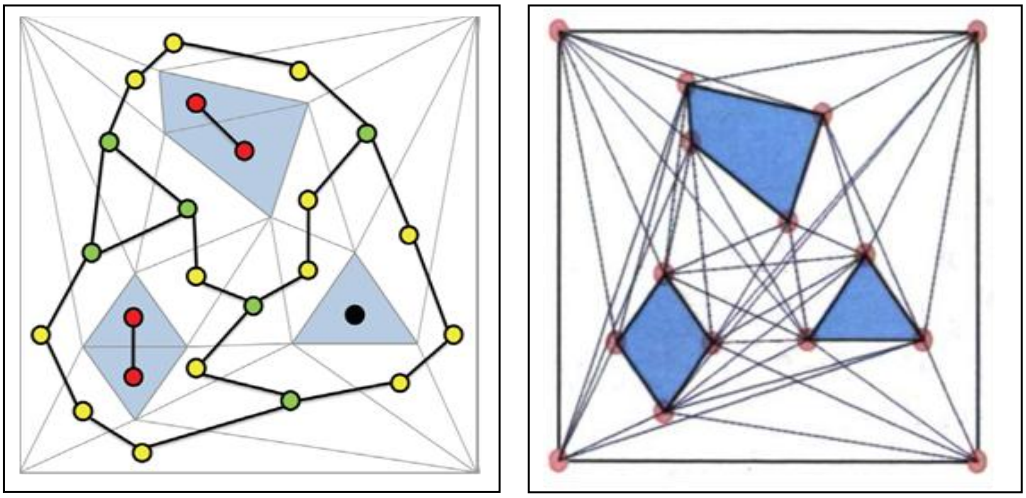
2.2.2. Rapidly-exploring Random Trees (RRTs)

RRTS [120] are similar to PRMs because they also randomly sample the (potentially high-dimensional) configuration space to build a graph of configurations, on which a graph search can be performed. A tree of valid paths is grown in Cfree from the start configuration using random sampling, until the goal configuration can be connected to the tree. Due to their random nature, RRTs seem ideal for creating different paths given a specific path planning query [121]. Unfortunately, the running time is prohibitively high and the resulting paths can be of low quality, rendering this approach inappropriate for gaming applications.

2.2.3. Visibility Graphs

In a visibility graph, each node represents a vertex of a polygonal obstacle in the environment, and each edge represents a visible connection between points. Two nodes are connected if they are mutually visible, or, in other words, if the straight-line segment between them does not intersect any obstacles, see Fig.3.3 (b). The resulting graph minimizes distances and provides minimum length paths. The complexity of building visibility graphs increases when dealing with complex environments with a large number of obstacles. To avoid redundant edges, a reduced visibility graph can be constructed by categorizing edges into supporting and separating edges [122].

However, some problems may arise from the fact that the edges of a visibility graph usually connect corners in the environment which can make the artificial entities in the environment to move too close to the walls or corners and maybe even collide with them [123].



(a) Roadmap generation using a Delaunay Triangulation [124].

(b) Computation of visibility graph. [122]

Figure 3. 3 Two examples of Roadmap approach

2.2.4. Generalized Voronoi diagram (GVD)

A Voronoi diagram [125] is a type of decomposition for metric spaces, determined by distances to a set of entities in the space. The edges of a Voronoi diagram represents all points equidistant to a pair of entities and a node is a point equidistant to three or more entities. A Generalized Voronoi diagram is a Voronoi diagram in which entities are sets. Generalized Voronoi diagrams are typically used for robot path planning.

2.2.5. Adaptive Elastic ROadmaps (AERO)

It is a connectivity graph structure that is lazily computed using a generalized crowd dynamics model [126]. Specifically, it uses a Generalized Voronoi diagram to compute a roadmap that defines the free space with respect to static geometry. The roadmap is continuously updated in response to the motion of the agents and the other dynamic obstacles present in the environment. The links between two points of the free space can be deformed in presence of a dynamic obstacle. Those links have a maximum elasticity and are broken (removed) when this value is exceeded, disconnecting both points. In Fig.3.4. The obstacle O1 is moving towards link l2 (left) and it is deformed (center). When the elasticity of the link is exceeded, the link l2 is removed (right).

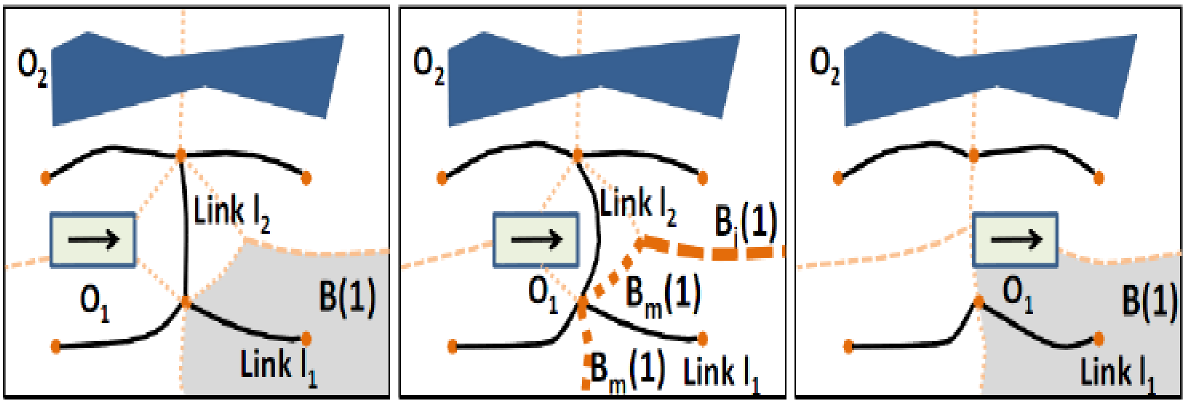


Figure 3. 4 Adaptive Elastic ROadmaps with moving obstacle [126]

2.3.Navigation Mesh

A navigation mesh (NavMesh), is a decomposition method that consists to encodes the free space of the scene by splitting it into convex polygons, known as cells. A Cell-and-Portal Graph (CPG) is obtained where a node represents a cell of the partition and a portal is an edge of the graph that connects two adjacent cells. By delimiting the free navigable regions, the navigation mesh can support path planning and also provide important spatial information that agents can use during collision avoidance and behavior execution [124].

2.3.1. The Constrained Delaunay Triangulation

Triangulations offer a natural approach for cell decomposition and they have been employed for path planning in varied ways. The majority of the methods using triangulations for path planning applications are however limited to simpler solutions based on the Constrained Delaunay Triangulation (CDT) as a cell decomposition for discrete search.

CDTs can be defined as follows. Triangulation T will be a CDT of polygonal obstacles S if: 1) it enforces obstacle constraints, i.e., all segments of S are also edges in T, and 2) it respects the Delaunay criterion as much as possible, i.e., the circumcircle of every triangle t of T contains no vertex in its interior which is visible from all three vertices of t [114].

A dynamic Constrained Delaunay Triangulation (CDT) is used to represent the walkable area of a scene. The method proposed also allows the incremental insertion, move and removal of obstacles, adapting the Navigation Mesh in consequence.

The main drawback is that many unnecessary cells are created, increasing the time for calculating a path between two given cells, which can be specially problematic in applications such as videogames, where a real-time response is required.

In [127] the CDT technique is compared against grid-based maps of real commercial videogames. The results show that the use of a CDT to represent the walkable space dramatically reduces the computation time to find a path between two points, compared to the grid representation of the same map. In [63], more uses of the CDT are explored, such as the automatic placement of agents in the free space and path planning with clearance.

2.3.2. Local Clearance Triangulation

Kallmann [50] introduced a navigation mesh called a Local Clearance Triangulation (LCT) that allows paths to be computed free of obstacles with arbitrary clearance. Such triangulation is obtained by a process that iteratively refines the Constrained Delaunay Triangulation (CDT) resulting from the starting set of obstacles.

The refinements are designed to ensure that two local clearance values stored per edge are sufficient to precisely determine if a disc of arbitrary size can pass through any narrow passages of the mesh. This property is essential for the correct and efficient extraction of paths with clearance directly from the triangulation, without the need to represent the medial axis.

LCT can be used to answer path queries for characters of different size. Locally shortest paths can be computed in optimal time. If global optimality is required, an extended search is used to gradually improve the path. Kallmann's navigation mesh [50] yields an exact representation of the environment and can handle dynamic updates efficiently. However, it introduces more cells in the partition of the scene, thus dropping the performance of the path finding algorithm, and (multilayered) 3D environments are not discussed.

2.3.3. Topoplan

Topoplan [128] is an application that automatically generates a Cell-and-Portal Graph for a given virtual environment defined as a mesh of triangles. It consists to apply a simplification phase consisting in representing the mesh with 3D planar polygons instead of triangles. Those polygons are computed by partitioning the set of mesh triangles into sets of coplanar and connected triangles. Then, an exact 3D prismatic spatial subdivision of the 3D model is computed. The aim of this approach is to organize a set of 3D polygons in order to capture ground connectivity and identify floor and ceiling constraints. It represents the environment by a set of vertical 3D prisms dividing the 3D model into layers. A Constrained Delaunay Triangulation is computed over each of this surface to obtain the final CPG usable for path planning. Although the description of the walkable space is perfect, it is very costly in time.

This work was then extended to identify outdoor, indoor and covered areas for spatial reasoning [129]. Jorgensen presented an automatic structuring method based on a hierarchy that separated buildings into floors linked by stairs and represents floors as rooms linked by doorsteps. This method has a strict hierarchy and does not scale to large outdoors environments such as the ones often presented in video games.

The main advantage of using a partition based on triangles is that geometric operations with triangles are very efficient, the convexity of the partition is guaranteed and it contains the least possible number of ill- conditioned cells. However, the partition is far from optimal as it is restricted by triangles.

2.3.4. Explicit Corridor Map (ECM)

Geraerts [130] created a navigation mesh called the Explicit Corridor Map (ECM) which is used to compute paths with any desired amount of clearance to obstacles and permits each character to have any desired size. Explicit Corridor Map (ECM) is an annotated data structure that describes the free space as related to the medial axis of the environment, which is the set of all points that are equidistant from at least two distinct closest obstacle points. The medial axis can be seen as a special type of waypoint graph in which all edges run through the center of the free space between pairs of obstacle polygons.

For each vertex of the medial axis graph, there are either at least three obstacle polygons that have the same distance from that vertex, or the vertex is placed in a non-convex corner of an obstacle. An edge between two vertices of the medial axis consists of a sequences of straight-line segments and parabolic arcs, depending on the type of corresponding obstacles to its left and right (with respect to a given orientation of the edges).

With each element in this sequence, its left and right closest obstacle points are stored. This partitions a 2D environment into a set of walkable areas in O(n log n) time and O(n) space, where n is the total number of obstacle vertices. Each area corresponds to one particular obstacle polygon, as all points in that area are closer to that obstacle than to all other obstacles [131].

Toll et al. [132] present a NavMesh generation method for a multi-layered environment, such as an airport or a multi-story car-park, where the different layers of the scene are connected by elements such as stairs or ramps. However, they do not provide an automatic method to extract such layers..

2.3.5. Clearance Disk Graph (CDG)

From the environment geometry analysis, Pettré et al. [18] compute a structure called Navigation Graph as shown in Fig.3.5. A Navigation Graph is a simple structure that represents an environment topology by distinguishing navigable areas from impassable obstacles. The Navigation Graph is composed of vertices and edges: the vertices are vertical cylinders representing areas where a pedestrian can freely walk without colliding with its environment. Edges are gates allowing a pedestrian to cross from one cylinder to another one. They are introduced between vertices wherever two cylinders overlap.

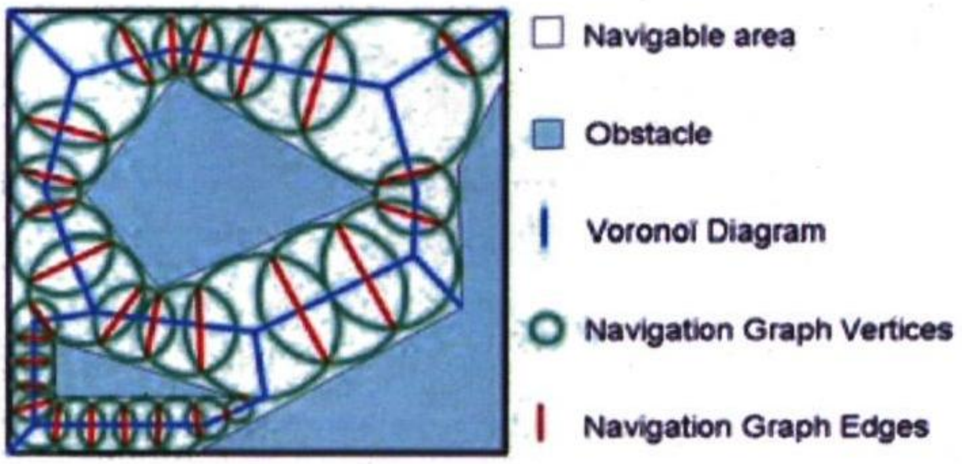


Figure 3. 5 Navigation Graph [18]

2.3.6. Navmeshes From 3d Geometry: Neogen

Oliva and Pelechano [133] describe an efficient technique to calculate a convex decomposition with a number of cells close to the optimum. It starts with voxelization, but it groups walkable voxels into 2D layers. Next, the method obtains a more precise floor plan for each layer in a way that does not depend on the voxel size. Based on these floor plans, an exact 2D algorithm [134] is used to compute the final navigation mesh. This 2D algorithm subdivides the layer into convex polygons in O(nr) time, where $r < n$ is the number of convex polygon vertices in the input. A contribution of NEOGEN is the convexity relaxation parameter that can be used to allow slightly non-convex regions. This decreases the total number of regions in exchange for having more complex region shapes. Clearance information can also be added to the navigation mesh if desired.

2.4. Other approaches for environment modeling

Shao and Terzopoulos [31] represent virtual environments by a hierarchical collection of maps: (a) a topological map, which represents the connections between different parts of the virtual world; (b) perception maps, which provide information regarding perceptual queries; and (c) path maps, which enable online path planning for navigation (Fig.3.6). The topological map contains nodes corresponding to the environmental regions and edges representing accessibility between regions. The path maps include a quad-tree map, which supports global, long-range path planning, and a grid map, which supports short-range path planning.

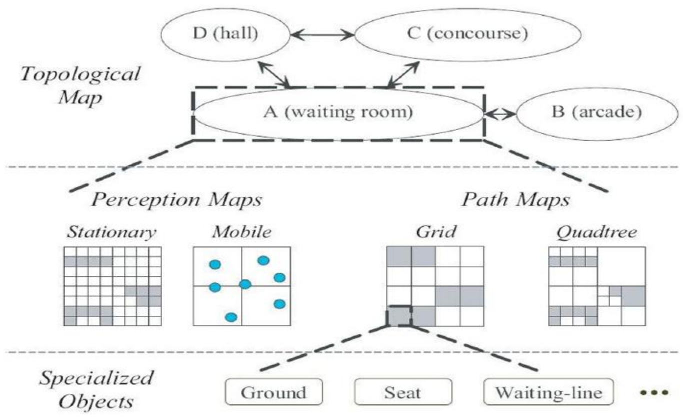


Figure 3. 6 Hierarchical representation of a building [31]

A novel hierarchy environment model is presented in [135] to represent multilayered complex virtual environment and ease the simulation task in such environment. It is illustrated in Fig.3.7, which includes comprehensive and sufficient environment information for simulating crowd in complex environment. This model is subdivided into three layers and will introduce them respectively in following paragraphs.

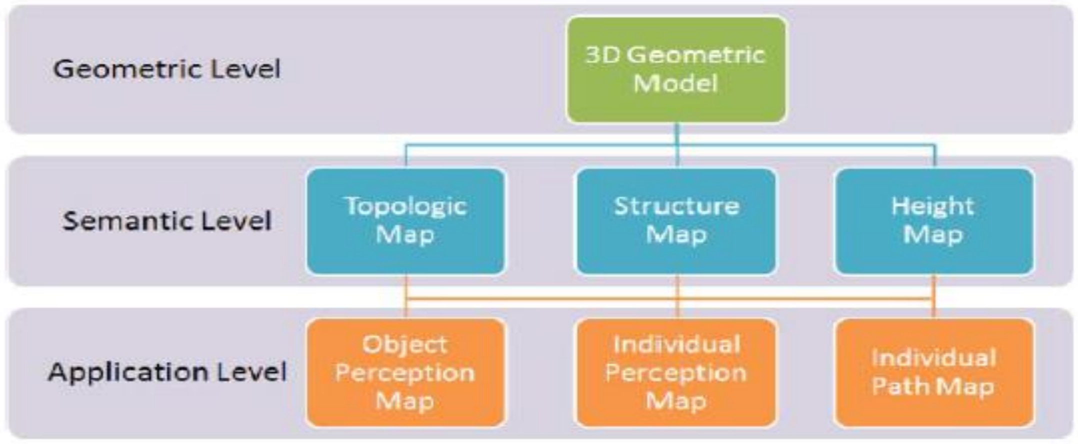


Figure 3. 7 A Semantic Environment Model for Multilayered Complex [135]

- ✓ Geometric Level: The main part of this layer is 3D geometric model of the environment that is employed for display and the semantic information extraction for the next semantic representation layer.
- ✓ Semantic Level: The semantic layer is composed of structure map, topologic map and height map which help to identify or query semantic information of the environment.
- ✓ Application Level: For the purposes of providing efficient interaction between pedestrians and the environment, this layer is responsible to use the information of

semantic level to generate some high-level maps such as object perception map, individual perception map and individual path map in the application level.

The topologic abstraction algorithm aims to generate an abstraction tree by merging interconnected cells while trying to preserve topological properties. The topologic abstraction proposed by Paris and Donikian reduces the size of the graph that represents the spatial subdivision [136]. The grouping process relies on the topological properties of the cells and the resulting graph contains fewer nodes and preserves the topologic and geometric characteristics of the geographic environment. However, the topological characteristics are not sufficient to abstract a virtual environment when dealing with a large-scale and complex environment involving areas with various qualifications (buildings, roads, parks, sidewalks, etc.).

3. Pathfinding

Path planning is a process of finding a the shortest or least effortful path between two distinct spots located in a virtual world. A path means an approximated way, composed by connected segments, that must have two properties [114].

The first property is called validity which is the most common measure to indicate whether or not the path is collision free.

The second property is called optimality which is measured normally by either a distance metric or the time required for travelling through the path. Using a distance metric, an optimal path is simply the shortest path. It means the distance between start and goal in such a path is no greater than any other routes. It is an intuitive requirement. Time is another widely used measure. It defines an optimal path as the fastest route. Simply it means the time required for an optimal path to be travelled through is always less than any other routes. In most cases, the shortest path is often the fastest one.

There are several path-finding techniques developed to plan path through complex environments. In the following section, we discuss the popular algorithms.

3.1.Dijkstra Algorithm

Dijkstra's algorithm was conceived by Edsger Dijkstra in 1959 [137]. This algorithm works by visiting vertices in the graph starting with the object's starting point. It then repeatedly examines the closest not-yet-examined vertex, adding its vertices to the set of vertices to be examined. It expands outwards from the starting point until it reaches the goal.

Dijkstra's algorithm is guaranteed to find a shortest path from the starting point to the goal, as long as none of the edges have a negative cost.

In Fig.3.8, we show an application of Dijkstra's algorithm in an 8-connected grid representation. The black segments depict the search tree that was explored until the highlighted solution path was found. The nodes marked as yellow disks represent the nodes in Q at termination time. In this environment brown cells represent obstacles and blue cells have a traversal cost higher than gray cells.

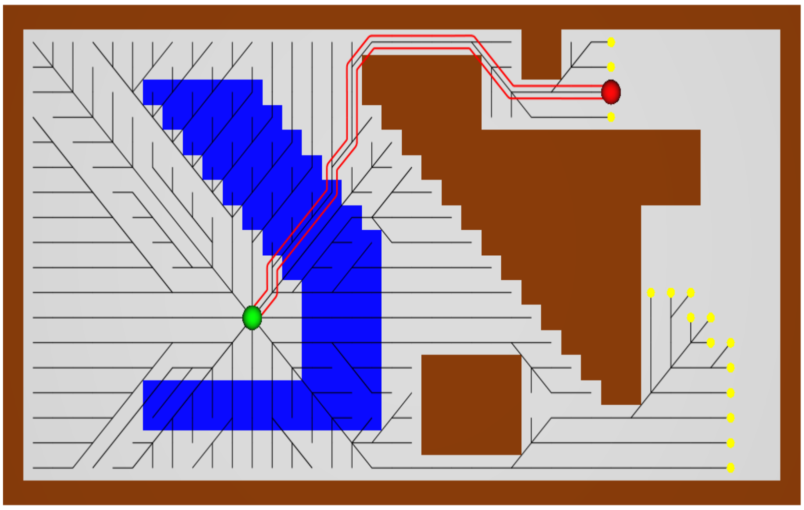


Figure 3. 8 Example of Dijkstra's algorithm in an 8-connected grid representation [114].

3.2. A*

A* is a generic search algorithm which is expanded from Dijkstra by applying a heuristic value [138]. This heuristic provides an estimate from a particular node to the final goal node. The algorithm focuses to combine actual traversal costs from a start node with heuristic values that estimate the distance to a target node. Using these two values, A* explores and exams the cell with the lowest estimated total cost:

$$F = G + H$$

where G is the distance from the start cell to the current cell and H is the estimated distance from the current cell to the goal cell.

A* manages two lists of nodes, the open list and the closed list. While the open list stores all nodes that are currently under consideration, the closed list stores all nodes that have already been expanded and do not need to be visited again.

A* paths are always optimal as long as the heuristic function is admissible. However its overall time depends on the problem size and complexity, resulting in highly variable times. The biggest drawback is that its response time is the same as its overall time as a complete solution is required before the agent moves. A*'s memory use is variable and may be high depending on the size of its open and closed lists and the heuristic function used.

3.3. Anytime Dynamic Search

A* search is an approach that uses a heuristic to restrict the number of states that must be explored before finding the optimal path and it guarantees to expand an equal number or fewer states than any other algorithm using the same heuristic. However, for large scenarios A* still needs to expand many nodes and can very quickly run out of memory [114].

Anytime planning algorithms start to find the best solution they can within the amount of time available to them. This first solution is an approximate, and possibly highly suboptimal plan which is improved over time by reusing previous plan efforts.

A popular anytime version of A* is called Anytime Repairing A* (ARA*) [138]. This algorithm performs a series of repeated weighted A* searches while iteratively decreasing a loose bound (ε). It iteratively improves the solution by reducing ε and reusing previous plan efforts to accelerate subsequent searches. However ARA* solutions are no longer guaranteed to be optimal.

Another anytime variant of A* is called Anytime Non-parametric A* (ANA*) [140]. It uses a novel criterion for deciding which node to expand next in each step. Instead of expanding the node with lowest weighted f-value, it expands the node that maximizes the term $e = (G - g)=h$, with G being the costs of the currently best solution (which is set to infinity in the first iteration). The term e can be intuitively understood as the ratio between the "budget" that is left to improve the current-best solution and the estimated costs between the node and the goal.

D* Lite [141] performs A* to generate an initial solution and repairs its previous solution to accommodate world changes by reusing as much of its previous search efforts as possible. D* can correct "mistakes" without re-planning from scratch, but requires more memory.

Anytime Dynamic A* (AD*) [142] combines the properties of D* and ARA* to provide a planning solution that meets strict time constraints. It efficiently updates its solutions to accommodate dynamic changes in the environment.

3.4. Hierarchical Path Planning

The computational effort required to find a path, using a search algorithm such as A* [138] or Dijkstra [137], increases with the size of the search space [143]. As a consequence, path planning on large-scale geographic environments can result in serious performance bottlenecks. However, representing the virtual environment using the hierarchical approach allows a reduction in the size of the search space as well as the problem complexity in path planning [144].

Demyen and Buro [127] present two hierarchical triangulation-based path-finding algorithms TA* (Triangulation A*) and TRA* (Triangulation Reduction A*). TA* makes use of the Delaunay Triangulation (DT) technique to represent maps in which obstacles are defined by polygons, and finds optimal paths for circular objects by running an A* like algorithm on graphs induced by the triangulation.

TRA* improves on TA* by applying a topological map abstraction that contracts each corridor in the triangulation graph to a single edge and tree components in which path-finding is trivial are removed and handled separately. What is left is a graph only containing degree-3 nodes. Its size is proportional to the number of obstacles on the map, which can be considerably smaller than the triangulation graph. Because of this size reduction, TRA* runs faster than TA* and much faster than A* on common game maps while generating high-quality paths.

An earlier hierarchical path-finding algorithm is HPA* [143]. This method decomposes a map into disjoint square sectors. Entrance points between adjacent sectors are identified and added as nodes into an abstracted search space. Fig.3.9 shows a small map. Abstract edges connect pairs of entrance points placed on the border of the same sector. In effect, in the abstracted space, a move traverses one sector in one step. Additional abstracted edges connect the start node (and the target) to the entrance points of its sector. An abstract solution contains macro moves such as sector-traversing moves. In a refinement step, a search restricted to the area of one sector converts a macro step into a sequence of actual moves. The method can have more than 2 hierarchical levels.

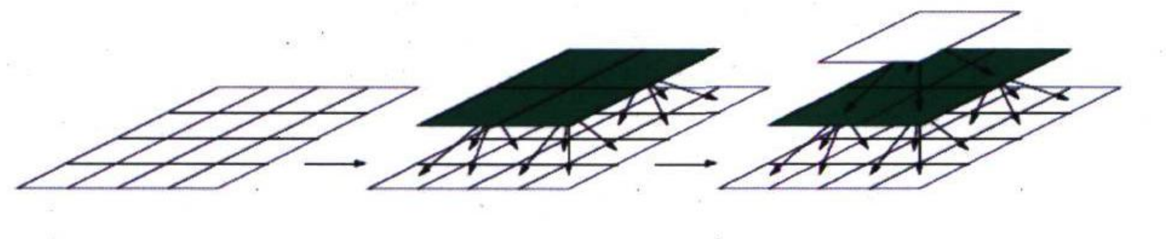


Figure 3. 9. Abstracting tiles into a hierarchy [143].

HAA* [144] extends HPA* in two directions. First off, in classical path-finding, a map is partitioned into traversable terrain and blocked areas. HAA* makes a finer distinction, allowing to define several types of terrain, such as ground, water, and walls. Secondly, HAA* handles mobile units with variable sizes and variable terrain traversal capabilities.

3.5. Multi-Agent Path-finding

Multi-agent path-finding addresses the problem of finding paths for a set of agents going to their goals. Each agent may have its own goal or all the agents may have a global goal. At each time step, all agents move according to their plans. The set of agents has to find the minimal cost for reaching the set of goals, or to maximize some quantity. The cost can be the elapsed time. Multi-agent path-finding can be cooperative, when all the agents help each other and try to optimize in the same direction. But it can be adversarial when an army tries to reach a point and another one prevents this from happening.

Silver [118] introduced the cooperative A* (CA*) algorithm, which allows agents to take into account the planned routes of other agents. The routes computed by other agents are stored in a reservation table, which is accessible by all the agents. However, this algorithm may have poor performance in complex environments.

Hierarchical cooperative A* (HCA*) uses the idea of Hierarchical A* [143] with the simplest possible hierarchy. It abstracts and reduces the research space: the domain with all agents removed. An issue of HCA* is how to terminate: sometimes an agent sitting on its destination must move to give the way to another agent. Another issue is the ordering of agents, and the most important one is computing complete routes in the 3-dimensional space.

Windowed Hierarchical Cooperative A* (WHCA*) algorithm is introduced in [118]. When an agent reaches its goal, it may continue to block the paths of other agents. WHCA* simply limits this by windowing the space search, which allows agents to determine partial routes to their goal. If an agent has reached its goal, it will try to find a terminal node within its current window.

4. Local Avoidance

Avoidance is a behavior that occurs when a human avoids another human (or obstacles) during the movement. Collision should be avoided locally by adjusting movements when other agents become sufficiently close. To achieve realism in crowd simulation, the local behavior of individuals must be modeled. Furthermore, simulating group behavior in pedestrian crowds should effectively combine collision avoidance with group coherence techniques. Local collision avoidance is an important aspect of micro simulation, since individuals are expected to adjust their planned route so as to avoid collisions with dynamic obstacles and other individuals. In the rest of this section, we discuss various approaches for local collision avoidance between simulated characters.

4.1.Reactive approaches

The most common way to solve interactions between virtual characters is with reactive navigation techniques. In such approaches, the character adopts its previously computed motion to avoid colliding with the dynamic and static obstacles found along its path.

In the animation community, the concept of reactive collision was introduced by the work of Reynolds who used simple local rules to describe interactions between autonomous agents [70, 37]. Closely to his work, Musse and Thalmann implemented a multi-resolution algorithm based on simple avoidance laws to handle inter-agent collisions [40], they focused on basic collision handling by proposing the following techniques.

- ✓ Collision avoidance type 1. The technique uses a simple mathematical equation to detect a possible collision event, it involves intersection of two lines and distance between two points. If two virtual humans are potentially colliding, the solution consists to stop one virtual human and let the other one to pass.
- ✓ Collision avoidance type 2. The method is straightforward and it depends on the change of directions. Instead of waiting for the other one, the autonomous virtual human can avoid the collision by changing its directions through angular changes. After a specific period of time, the virtual human returns to its last angular velocity.

Another collision technique is proposed by Loscos et al. [145] for crowd system. This technique uses grid-based rules depending on parameters such as density, speed and direction to resolve collisions between virtual pedestrians and others object (such as building). The technique outlines three types of collisions strategies which are frontal, following and perpendicular. The technique compares the direction of each agent, the velocity factor and the distance between the agents. In order to deviate from an appropriate angle, there are a few ways to decide either to slow down or to completely stop.

Rymill et al. [146] describe a system designed to simulate human behavior in crowds in real-time, concentrating particularly on collision avoidance. There are three possible types of collision, which here will be called Towards, Away and Glancing; these are shown in Fig.3.10:

- ✓ A Towards collision occurs if the actors are walking towards each other.
- ✓ An Away collision is, conceptually, when the subject is behind the collidee, but is gaining on them.
- ✓ A Glancing collision is a side-on collision between two actors walking in roughly the same direction,

Based on the psychological input, Rymill et al. [146] showed that when a human avoids oncoming people, there are three different ways of avoiding the collision: changing direction only, changing speed only, or changing both direction and speed. They also stated that when a human avoids another human moving in the same direction, there are two options available; overtake or slow down and walk behind the people in front. To resolve the glancing collisions, the pedestrian tries a variety of direction and speed changes, in an attempt to find a course that will avoid a collision occurring. If no such course can be found, the subject is forced to stop until the collidee has passed.

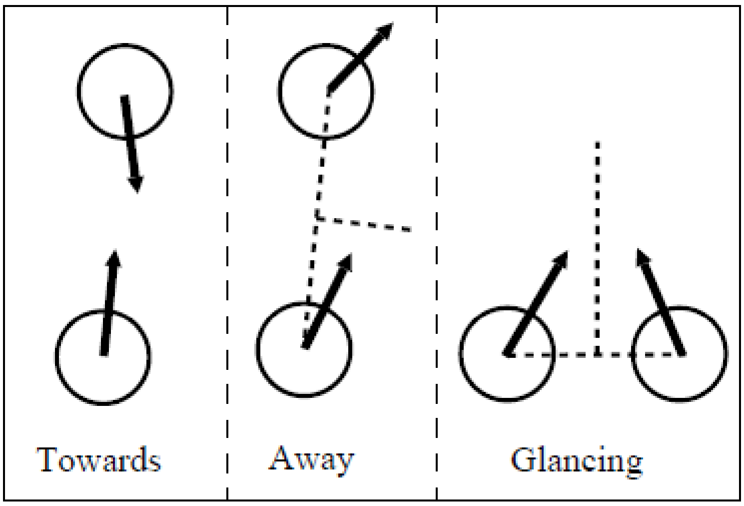


Figure 3. 10 Three different types of collision [146]

Cherif et al. [147] applied the avoidance behavior based on forces of attraction and repulsion in the agent. The avoidance behaviors that consist of avoidance of collision and avoidance of obstacles were affected by the type of situation (normal and panic), the personal space (broad, average and narrow) and the level of patience that were influenced by a set of psychological and sociological rules in the model.

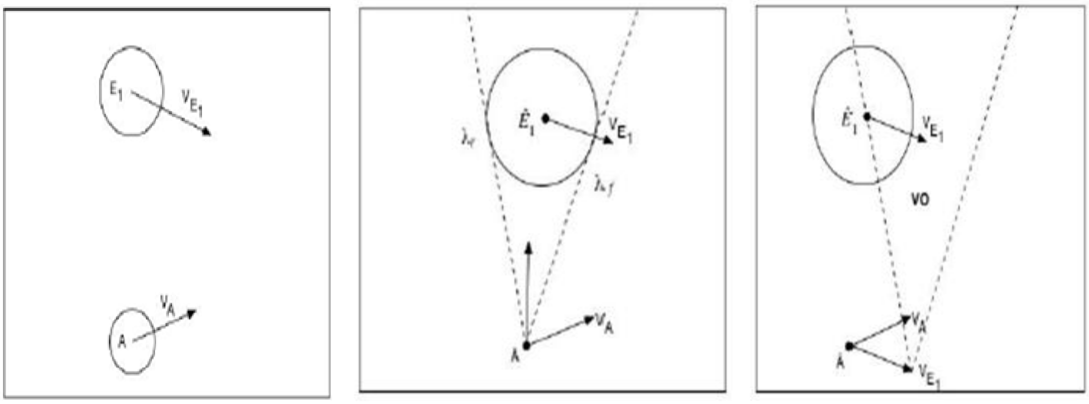
4.2. Velocity-based Local Collision Avoidance

These methods use the current position and velocity of each mobile robot or virtual agent to estimate its future trajectory for some short window of time and compute a new velocity that will be free of collisions over some short time interval. Often, the new velocity for each mobile robot or virtual agent may be computed independently without explicit communication, allowing for distributed systems of mobile robots or the parallelization of simulations of virtual agents on modern multi-core architectures.

Fiorini and Shiller [48] introduce the concept of the velocity obstacle (VO) to define the set of velocities that would lead a robot to collide in the future with its static and dynamic environment. This approach considers a single reactive agent (the robot) and the rest of the dynamic obstacles are assumed to be passive. Fig.3.11 shows how VOs are constructed. First, the size and velocity of agent A and obstacle E_1 are known (Fig.3.11(a)). Then object A is reduced to a point, while E_1 is enlarged by the radius of A. Next, two tangents are constructed that enclose the Collision Cone.

Any relative velocity $\mathrm{v_a} - \mathrm{v_{E_1}}$ that lies inside the cone will lead to a collision (Fig.3.11 (b)). Shifting the Collision Cone by $\mathrm{v_{E_1}}$ results in the VO (Fig.3.11 (c)). To prevent a collision, A must choose a velocity that lies outside of the VO. Multiple obstacles can be included in the decision process by combining the VOs.

The technique is commonly used in computer games and closely tied to robotics research. In systems where each robot works independent of a central planning authority, such algorithms are a means of preventing collisions between agents. Unfortunately it can suffer from oscillations, where agents repeatedly attempt to evade each other.



(a) Colliding agents. (b) Collision cone. (c) Resultant velocity obstacle.

Figure 3. 11 Velocity Obstacle construction [48]

Van den Berg et al. 2008 [148] extend the VO approach so as to achieve collision avoidance between multiple robots that navigate in a planar environment. For this reason they base their method on the concept of reciprocity, i.e. each agent assumes that the rest of the agents follow the same avoidance reasoning. By examining all possible pairs that an agent can form and then by intersecting the allowed new velocity spaces, each agent selects its new velocity as the allowed velocity that is closest to its desired velocity.

Karamouzas and Overmars [149] present a different velocity-based approach for realistic collision avoidance among virtual characters. This approach is derived from the empirical observations of Pettré et al. [148] and is based on the simple hypothesis that is an individual tries to resolve collisions in advance by slightly adapting his preferred direction and speed. The authors subsequently perform an experimental analysis on the existing motion capture data to gain a better understanding into how humans solve interactions and avoid collisions with each-other in real life. This analysis, though, focuses on the predicted time-to-collision between interacting participants and the deviation from their desired velocities, whereas they studied the effect that the minimum predicted distance has on the participants' accelerations.

Additionally, this method employs the predicted time-to-collision thresholds to define the permitted velocities and orientations throughout the collision avoidance stages using piecewise functions that match the observations. These permitted velocities and orientations are then optimized based on a criterion that jointly minimizes energy consumption, collision risk, linear and angular acceleration. A limitation of this method is that it employs axis aligned boxes to model the static obstacles, can thus lead to a crude approximation of the non-navigable space.

Karamouzas et al. [149] introduced the evasive force to improve the social force model. Their approach is based on the hypothesis that an individual adapts its route as early as possible, trying to minimize the amount of interactions with others and the energy required to solve these interactions. With this model, the agents do not repel each other, but rather anticipate future situations avoiding collisions long in advance and with minimal effort. However, the applications of social force model are limited by the calculation efficiency because of its complex rules.

Paris et al. [150] proposed an anticipative collision avoidance method, they generated a series of time-dependent workspace obstacles by linearly extrapolating the obstacle's velocity. These workspace obstacles cast a shadow on the velocity space; the velocities in that shadow are those velocities which would collide with the workspace obstacle during that time interval. The feasible region in front of the shadow contains velocities which would cause the agent to pass behind the moving obstacle. The region beyond the shadow contains those velocities which would cause the agent to pass in front of the moving obstacle. Finally, the segments are reconciled across multiple moving obstacles, ranked according to a cost function, and the "best" section is used to produce a final velocity.

Koh and Zhou [151] introduced a collision avoidance framework called relative frame. According to the duality property of the relative frame and other constraints, they selected a collision-free velocity for an agent.

4.3. Vision-based approaches

More recently, vision-based methods have been presented as an attempt to better simulate the perception model of pedestrians and their corresponding motion planning mechanisms. Ondřej et al. [152] propose a collision-avoidance technique that is based on a synthetic-vision perceptual model. Collision avoidance is based on the bearing angle between a moving pedestrian and an obstacle, and the remaining time-to-interaction. When the remaining time-to-interaction is large, avoidance is achieved by maintaining the speed and altering the direction of motion. On the other hand, when the remaining time-to-interaction is small, then the agent decelerates until it stops to avoid an imminent collision. The method computes the desired angular velocity by attempting to both avoid the obstacles and deviate as little as possible from the goal direction. Only when the time-to-interaction of the most imminent collision is below a threshold value, then the speed of the agent decreases exponentially.

As an alternative, Moussaïd et al. 2011 [153] introduce a collision-avoidance method that is based on cognitive science approaches. They employ two vision-based behavioral heuristics to simulate the perception of pedestrians and their corresponding decision making processes throughout navigation. At each simulation step, an agent computes the time that corresponds to the most imminent collision for each candidate direction. Then, based on the first heuristic, the agent determines its desired direction of motion by trying to minimize the distance from its destination when a new directional change is expected due to the presence of an obstacle. The new speed of the agent is chosen based on the second heuristic, which dictates that the agent should maintain a distance from the first obstacle on the chosen direction that corresponds to a time-to-collision of greater than or equal to the relaxation time. Should unpredicted collisions occur with other agents or obstacles, physical forces are applied to simulate the interactions between the colliding entities.

5. Conclusion

The pathfinding problem that is persistent in many applications involving agents in virtual environments was discussed. It has been mentioned that agents require an abstract representation of the environment in order to navigate through the environment. These typically take the form of graphs. Graph search strategies or algorithms are then used to find routes through the environment. Having a graph with many nodes creates computational overhead as the size of the search space increases. Therefore, it is necessary that the environment be effectively decomposed by using a suitable division scheme.

Chapter 4: Agent-based model for modeling crowd behaviors

1. Introduction

Crowd simulation is a field that has recently been gaining significant attention because of its usefulness in various applications, such as emergency planning and evacuations, designing and planning pedestrian areas, subway or rail-road stations, besides in education, training and entertainment. There are a number of different computer simulation models which are typically developed to modeling of human crowds.

The core problem of these models is to build an efficient and accurate simulation of the movement of the crowd and each pedestrian in crowd. In this sense, the realism of the pedestrian's navigation behavior will affect the accuracy and reliability of the simulation results (e.g., the total time required to evacuate a building).

In this chapter we describe and explain how pedestrians navigate and move around virtual complex environment. In order to simulate such scenarios in detailed level, this work proposes an agent-based model for simulating the behavior and movement of pedestrians, the pedestrians are usually represented by autonomous agents whose movements are driven by a navigation model.

We proposed a hierarchical navigation model to describe the movements of a pedestrian. First, during the simulation process, each virtual pedestrian needs to select a goal as its destination the macro-level navigation model is used to compute a path (not necessary shortest) to a destination based on various influences that may affect route choice. Second, the micro-level navigation model is used to compute new steering parameters for the agents. Important pedestrian navigation behaviors like collision avoidance and overtaking are generated by the micro-level navigation model.

In Section 2 we describe our agent-based proposed model. Then, we describe the physical environment model (section 3) and the pedestrian navigation model for generating realistic navigation behaviors (section 4). We describe various behavioral characteristics, physical and psychological factors that affect the navigation behaviors of a pedestrian. Finally the chapter is concluded in Section 5.

2. Agent based model for crowd simulation

In general, Crowds are regarded as complex dynamical systems composing of heterogeneous groups of people, in which each person has individual and social properties, and interacts with others through different means. This observation indicates that human behaviors are highly complex and exhibit large variation based on situations and settings. Such behaviors are more complicated to be described in formal mathematical equations because of the dissimilarity of individuals and the non-linear nature of social and physical interactions between them.

According to this fundamental abstraction, we adopt an agent-based modeling methodology to develop an efficient model for generating realistic crowd dynamics with a wide variety of individual, and emerging behaviors during real time simulation. This model of crowd simulation constitute of several components and sub-components. At the most basic level, two key components are modeled: an environment model and a model of virtual pedestrians involved (Fig. 4.1). This model along with the computational methodology allows us to build an artificial environment populated with autonomous agents, which are capable of interacting with each other.

Environment model. The representation of the space of a model is tightly supported by setting up the following components:

- ✓ Geometry sub-component is the basis of the space representation model, it is, as its names implies, 3 dimensional Euclidean environment that allows people to move and occupy space. Movement can be either in all three dimensions (for example birds, fish, etc.) or only in two dimensions (for example herds, humans, etc.) This two dimensional movement could be approximated with only two dimensional space. The main part of this layer is 3D geometric model of the environment that is employed for display and the semantic information extraction for the next semantic representation layer.
- ✓ Topologic space subcomponent: is responsible to describe the connectivity and adjacency between separated regions in the interior space such as rooms and hallways.
- ✓ Structure map: In a complex environment, there are numerous objects, like handrails, walls, windows, pillars and so on, distributed widely in different regions. In order to facilitate organization and implementation, we divided the whole space into several independent but adjacent regions according to common sense. We called these

naturally separated regions, like an entire floor, stairs, or a corridor, as Block, and all the objects placed in the same region are included into the same block. All blocks along with their objects are organized into structure map.

- ✓ Points of interest. Points of interest are locations to specify the destinations of pedestrians in the virtual environment. Pedestrian needs to select one of them as its goal to achieve.
- ✓ Situational context. We have defined a simulated situation using chosen classes of the situation like navigating in normal conditions, or escaping evacuation context

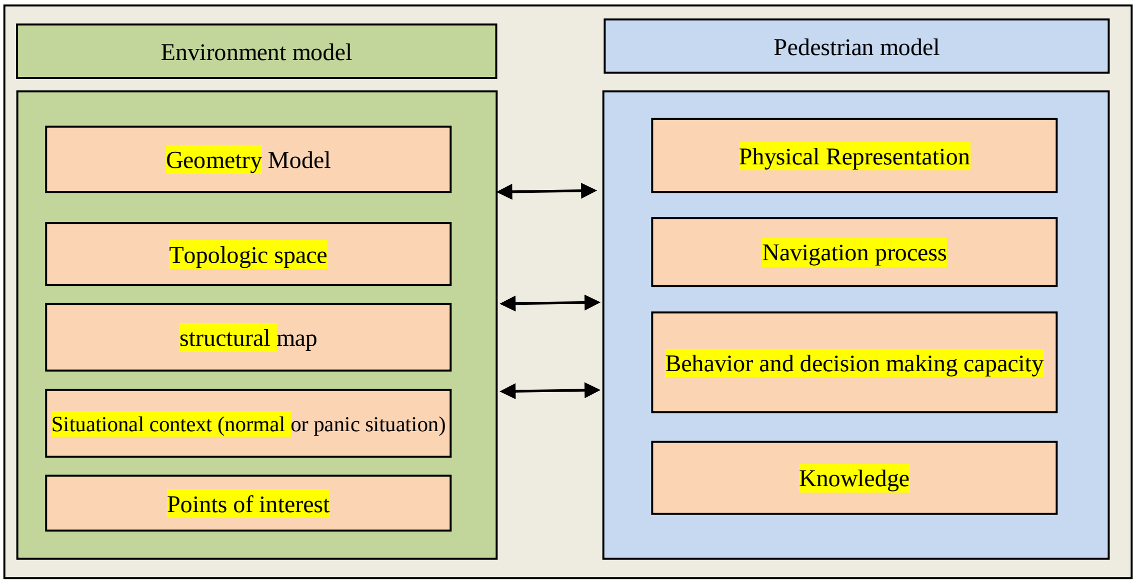


Figure 4. 1.Conceptual of our simulation model including setup of environment and agents.

Model of the individual: The model of the individual is the most important part of an agent based crowd simulation and there are a wide variety of ways in which this can be done. There are a variety of things to be considered when a human is being modeled. These include:

- ✓ Physical Representation: This refers to the physical characteristics of the humans being like the shape and size of the model used. Some papers suggest that for accurate modeling an elliptical shape is best but to make this computationally efficient a 3 circle model can also be used. The speed of movement of the humans and the time taken for pre-evacuation behavior can also be considered to be part of the physical representation.
- ✓ Navigation: Navigation refers to how the agents move within an environment. Depending on the scale of the environment, this generally consists of a higher level

path planning which is generally A-Star and a lower level collision avoidance algorithm. The choice of collision avoidance algorithms can have significant effects on the dynamics produced.

- ✓ Knowledge: Knowledge represents the agent’s familiarity with the surrounding environment which comes from a spatial analysis of the agent’s awareness range, varying from the individual’s vision to the entire scene. The agent makes his strategy, e.g., path selections, according to his knowledge.
- ✓ Behavior and decision making capacity: This refers to the detail in which some of the basic behavior is modeled in a crowd simulation. This also refers to the social interactions that takes place between the pedestrians.

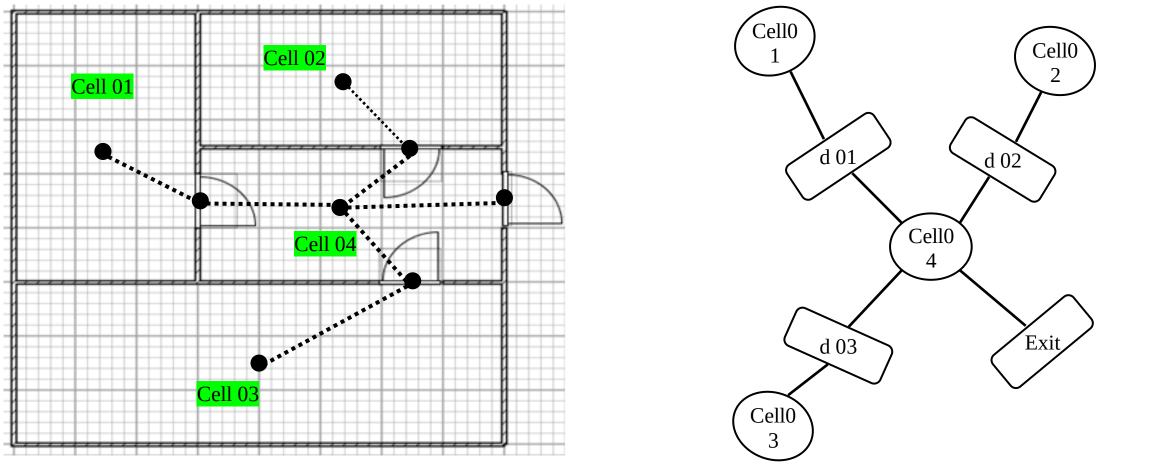
3. Environment Model

We use two basic ways to represent the geometry, i.e., the building, in our crowd simulation model. In this section, these two approaches are called coarse network (Connectivity graph), and fine network (Dual graph of quad-tree representation). Each approach is associated with its own distinct advantages and disadvantages, which will be explained more thoroughly below.

3.1. Connectivity graph for indoor navigation

When designing an efficient algorithm of the navigation process, the first step is to obtain the environment structures, and then construct a navigation-based topological data model. The topological data model, called connectivity graph, is a dual graph representing the spatial relationships among geographical objects, including connectivity, and adjacency, it consists of objects (nodes) where some pairs of these are connected by links (edges). In this data structure, the navigation process becomes a problem of getting from one node of the graph to another through a sequence of nodes and links.

Each node is typically a representation of contiguous physical region defined by their enclosing walls, e.g., a room of a building or a corridor, but can also represent connection between areas, e.g., a door opening. Each link (edge) represents the accessibility issue constrained by the existence of a route between two nodes (Fig. 4.2).



(a) Architectural map of our environment. Decision points and direct segments between them

(b) Topological graph. The decision points are nodes and Portals are edges.

Figure 4. 2 Floor Plan

3.1.1. Determining the Components of the indoor environment

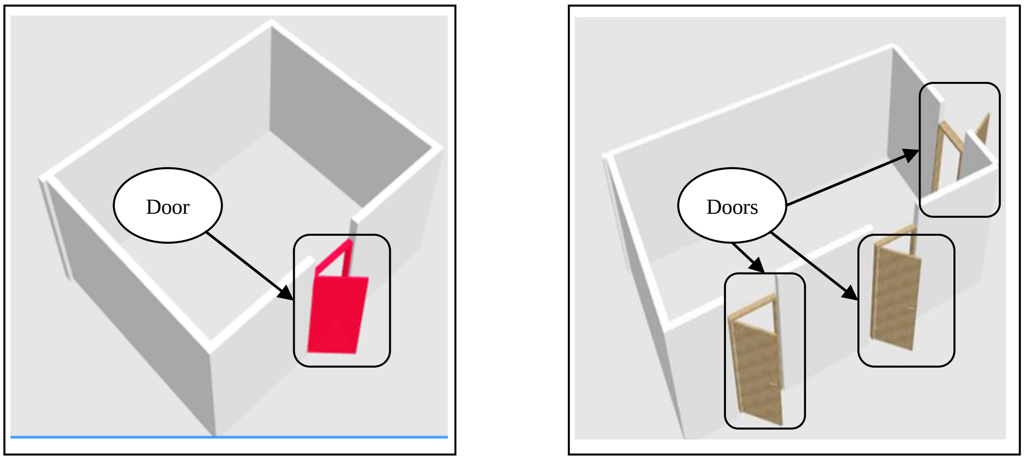
We now describe the representation of the various elements in our data model, and we will explore the shortest path segments in different kinds of zones according to their geometric shapes and architectural constraints, which can support shortest path routing.

a) Zones

There are a number of different kinds of architectural zones in indoor space. Some of them have similar shapes but may serve different purposes, and some of them are totally different in shapes but may play the same role during the routing. Specifically, we explore two different categories of zone according to their geometric and architectural features from the routing perspective; rooms with multiple doors can be a part of a passage to a certain destination, while rooms with only one door cannot.

- ✓ **Simple zone.** A simple zone is a zone that is closed by walls and can be accessed by only one door. A door is an architectural constraint controlling the accessibility of the zone. Since a simple zone has only one door, it cannot function as a passage. Thus, it can only play the role of a start object or a target object. Fig.4.3(a) shows an example of a simple zone. The solid boundary represents walls.
- ✓ **Complex zone.** A complex zone is a zone that is closed by walls and can be accessed by multiple access points. A complex room can be considered as either a start object, a target object, or an object that contains paths as passages to destinations. Fig.4.3(b)

shows an example of a complex zone. Multiple doors represent multiple decision points.



(a) Simple Zone (unique door)

(b) Complex Zone

Figure 4. 3 Architectural zones in indoor space

b) Doors

Doors represent an object that connects between two different spaces that are physically separated by a barrier.

3.1.2. Generating the topological graph

In this section, we describe the procedure for populating the data model with adjacency information. This involves constructing in the graph, nodes to represent decision points, links to represent connections between different decision-points (implicit or explicit direct segment from one zone to the other). Fig.4.4 visualizes the general principle of the generation of a topological graph step-by-step.

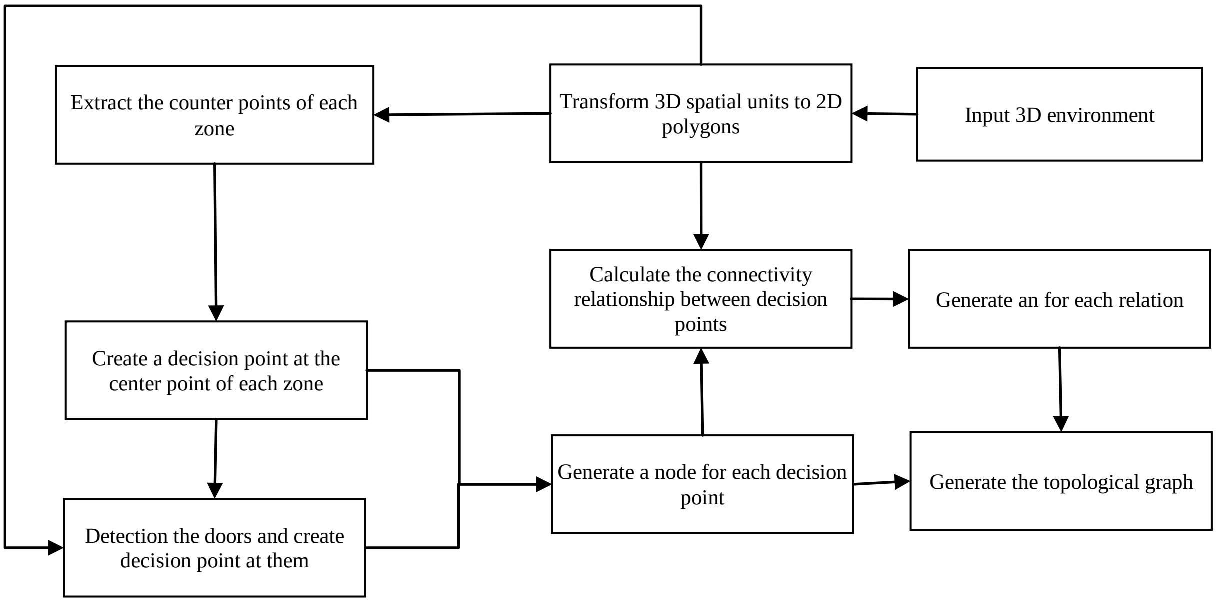


Figure 4. 4 Steps of the generation of a topological graph

a) Generating the nodes

Before the zones or doors are extracted, a building model is preprocessed as follows:

(1) The internal spatial units of the building are represented as 3D objects with flat top and bottom faces that are parallel to the horizontal plane, and their facades are parallel to the vertical axis.

(2) This step converts the 3D objects of the environment into a 2D map containing all constraints delimiting obstacles under the assumption that the environment is flat. This extracts all geometry belonging to the navigation area. After projecting the 3D units' vertices onto their corresponding floor planes, we determine the boundary points from the projection of the unit by eliminating the overlapping vertices.

(3) A zone has a set of contour points defining its polygonal boundary. Then for each zone, we extract their counter points, compute their dimensions and generate a decision point at its center.

(4) The last step involves the detection of doors, we are defining a door whenever a pair of Spaces is found to be adjacent and no physical barrier prevents direct traversal from one Space to the other.

b) Generating the arcs

After extracting the environmental units, we must compute the topological relationships among the units, topological features represent the relations among the discrete 3D objects. The most important topological relation is the inclusion relations between decision points. The following contents illustrate how to generate topological features by exploring the shortest paths between any pair of access points in different cells.

The approach to determine implicit path segments is based on the shapes of zones and the locations of access points. If a zone has one or more access points, and all of them can be directly reached from the center of the zone, we obtain multiple implicit path segments in the cell. The shortest path segments in this zone are all straight lines connecting its center and the access points. However, in the case, when an access point may not be directly reachable from the zone center (straight line connecting them is blocked by the boundary of obstacle), our approach to obtain the shortest path in this kind of situation is to select one of the boundary vertices on the contour of obstacle as an intermediate point, and partition the straight line into two segments. The partitioning process continues until all the generated segments do not intersect the boundary of obstacle.

c) Semantic feature

Nodes and arcs in connectivity graph model can be given specific characteristics in order to get more realistic representation of the geometry.

Nodes can be given a capacity, e.g., a maximum number of agents allowed in the node, in order to restrict the number of people occupying a certain area of the geometry. Specifying a node capacity can be essential in order to avoid unrealistic overcrowding.

Every edge represents a link between any two connected nodes, any two locations between two connected nodes in the graph are visible from each other in the indoor space and can reach each other without encountering an obstacle like a wall. The length of each edge in a graph is the value of the attribute length stored with each path segment. It is calculated by using the Euclidean distance $\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$ where (x_1, y_1) and (x_2, y_2) are the coordinates of the two decision points. The length of the edge is used to calculate the time needed to traverse this edge during an evacuation.

3.2. Quad-tree

For generating a fine network model, we use a quad-tree approach to represent the environment. Quadtrees are generated by repeatedly dividing each grid cell in a square grid into four equally sized grid cells. The division process terminates when a grid cell contains no obstacles, or when it reaches some smallest allowable size [117].

At the root level, the bounding box represents the entire scene. The scene is then recursively divided into four sections stopping only when the maximum number of levels is reached or when the content of leaf nodes is entirely homogenous; containing exclusively accessible or inaccessible regions. The number of levels determines the overhead needed to find a leaf node.

At the leaf level, spatial proximity information is maintained by storing links to the spatial neighbors of the leaf. This allows the path-finder to locate the next node easily.

The leaf nodes of the quad tree therefore forms a directed graph whose edge stores the cost of moving from one node to the next. The connection between different leaf node is established by joining the waypoints on the neighboring leaves.

4. Virtual Pedestrian Model

One of the fundamental objectives for the research in virtual humans is to demonstrate realistic navigation behaviors in a crowd scene, to correctly simulate this behavior in real time, it is important to propose an accurate representation of a pedestrian that can be used for several applications with believable and coherent behaviors.

Agents with the most complex visualization have 3D graphics body representations and are able to perform certain low-level actions, such as the playing of pre-recorded body animation sequences (such as gestures or changes of postures), walking to a specified location, looking at specified places. Higher-level behaviors are then composed of particular combinations of these low-level actions.

Agents contain a set of internal attributes that can correspond to various psychological or physiological states needed to model particular scenarios (such as memory, fear, mobility, or level of injuries), a set of higher-level complex behaviors (such as wander, flee or follow path) and a set of rules determining selection of these behaviors.

Agents can interact with both static and dynamic parts of the environment. Interaction between the agents and the static environment is done by a shared path-finder module which allows agents to move around the scene in the correct way. Interaction between the agents and the dynamic objects is done via perceptual interactions (e.g. agent perceiving danger at a specified distance from the threat).

4.1. Pedestrian behavioral characteristics

In this section, we review the most important pedestrian behavioral rules which are usually taken into account in crowd modeling to facilitate the simulation process. Modeling crowd dynamics requires to identify at least the most important behavioral rules pedestrians are subject to. It is plain that a pedestrian, as a complex living being, is basically unpredictable. Nevertheless, some guidelines can be drawn.

- ✓ Pedestrian is an intelligent character, it has the ability to decide its behaviors in different specific contexts, this refers to the process by which the person evaluates the perceived information about the world around it, produces and or/ selects movements according to its own status.
- ✓ Virtual pedestrian is defined as an independent individual. Pedestrian must display various behaviors in its unique style, for this it is characterized by set of individual parameters to differentiate it from others. Such diversities will be efficiently enough to result in differences in decision making process and movements.
- ✓ Pedestrian is an active entity. This indicates a pedestrian acts automatically and has a specific strategy to make its own behaviors. Under normal condition, it needs to follow naturally a route without detours and to move with its own individual, most comfortable walking speed for reaching its goals in precise time. However in the panic situations, the pedestrian exhibits an aversion to walking faster than usual, taking detours more often or moving opposite to the desired walking direction.
- ✓ Target. In most of the cases, people move in a bounded space and have a desired destination to be reached. This destination, together with the geometry of the space, defines a desired velocity field which is exactly the velocity people would keep if they were alone in the domain. The desired velocity can be very different whether the pedestrian under observation knows the domain or moves in a unfamiliar environment. The final velocity field pedestrians actually follow will be given by a suitable combination of the desired velocity field and the interaction velocity field, defined taking into account the following features of pedestrians.

- ✓ Repulsion. People want to avoid collisions, so they stop when they are too close to other people. Moreover, they have a tendency to avoid crowded regions, as well as to stay clear of walls and obstacles. Often mathematical models take into account this behavior by assuming the existence of a fictitious repulsive force which drives people toward clear spaces.
- ✓ Attraction. Sometimes people have the tendency to follow other people or simply stay in touch. This is the case of social groups like friends, families, tourist groups, and so on. For example, small groups of walking friends want to reach their destination all together, while keeping eye-contact and speaking with each other. Instead, tourist groups want primarily stay in touch with their guide (i.e. the sole person who knows the destination) and then keeping the group itself cohesive.
- ✓ Walking Direction and velocity. People have the tendency to keep the same direction of motion, since changing direction is tiresome and usually inefficient. This is one the reason which makes walking through a crowd an annoying task. A pedestrian determines the walking direction and velocity according to two principles, respectively [153].
    - o The desire for a fast walking. Naturally, pedestrians desire to reach the destination in a shorter time, and the direction pointing to the destination is preferred. However, obstacles and other pedestrians might locate on the direct path, and a trade-off has to be found between avoiding obstacles and minimizing detours from the most direct route. The desire for a fast walking inspires the determination of direction.
    - o The requirement for a safe walking. A time period s is required for the pedestrian to slow down in case of an unexpected obstacle, and pedestrians should compensate for this delay by keeping a safe distance. The requirement for a safe walking inspires the determination of velocity.
- ✓ The human navigation process is described typically through hierarchical movements in multiple layers of decision making, path planning determination and local path following. In everyday situation, the navigation behavior of pedestrians is usually not executed at one time. On the contrary, they divide the whole journey into multiple small parts in order to set many local intentions, and then find out a comfortable way to achieve each of these intentions by running a sequences of basic actions. It refers to

achieve a specific goal as a large-scale or macro-navigation, which includes path planning and way-finding behaviors to identify a rough route from the source to the destination. To perform the macroscopic movements, microscopic local movements such as collision avoidance and shortest path selection take place.

4.2. Physical and sociological pedestrian characteristics

- ✓ **Geometric representation of pedestrian:** In order to generate a most realistic simulation, the pedestrians' external appearance was described by a complex 3D model (such as mesh model), the physical size of a human body determines the plan view of an average adult male body by considering only his body depth and his shoulder breadth. We did not make distinctions between the agents on this point, setting the dimensions to 0.5 x 0.3 m.
- ✓ **Visual Field.** People have a limited visual field. It is usually assumed to be an angle of 170° or 180°, where the central area is sharper than the lateral ones. The line which divides in two equal parts the visual field can coincide with the actual direction of motion or, instead, with the desired direction of motion, and it is obviously related to the head orientation. If, on the one hand, the assumption that people can see only in front is reasonable, on the other hand it must be noted that people can turn their head, thus perceiving almost all the space around, and that other senses than sight can be involved, like, e.g., hearing and touch. Visual field is also limited by any obstruction people can perceive, like walls, columns, and other pedestrians themselves.
- ✓ **Sensory Regions.** In normal conditions, people do not interact with the others by contact, as mechanical particles do. Rather, they observe the surrounding space and take decisions.

  Sensory regions, which are in general different from the visual field, represent the portion of the space effectively considered before taking a decision, and can be different from need to need. For example, pedestrians are mainly repulsed by other people walking both close and in front to them, or by people walking on a "collision course", while they are little or no repulsed by far-away pedestrians, even if they are in the visual field. Then, repulsive sensory region is usually short-range and anisotropic. Attraction, instead, can be much more extended in space, even up to the whole visual field.

Sensory regions are one of the main ingredients of the mathematical models and sometimes make the difference among them. Indeed, changing the shape of the sensory regions defined for the various tasks leads to major differences in the simulated pedestrian behavior.

- ✓ **Pedestrian Personal Space:** Originating from psychological studies, personal space indicates the invisible area surrounding individuals. The concept of personal space is considered as a social factor that strongly impacts communication or contact between people. This free zone, which has the shape of a parabolic curve, is influenced by several parameters such as the pedestrian body's size, his wanted walking speed, the density of the surrounding population and his acquaintances with his neighbors (social relations, familiarity, etc.), etc.
- ✓ **Position**. These are the location coordinates of a specific point related to an origin. This is not as simple as it might seem, because bodies have a volume, so which exact position a body has, is a controversial discussion. Normally the centre of mass is used to determine the position, but other points can be used depending on the approach. In order to calculate the movement, we need to know the rate of change of the position, both the magnitude and the direction.
- ✓ **Velocity**. This is the current velocity that an agent possesses and, contrary to the strength, this attribute has both magnitude and direction. This is the rate of change of the agent's location; thus, it is used to obtain the next position. It is calculated with the acceleration that the total force produces on the agent.
- ✓ **Maximum Speed.** This is the higher punctual speed that an agent can move in the world with. Do not confuse this with how fast an agent can change of physical state, which is related with forces and mass (acceleration). Consider the next example: a cheetah can change from 0 to 100 km/h in a matter of seconds (high acceleration); on the other hand, a high-speed train, which needs a lot of force (strength with direction) to move such a big mass, has much smaller acceleration, but it can travel at 200 km/h (high maximum speed).
- ✓ **Vision Radius.** This property determines which portion of the world the agent is aware of. This is mainly used to calculate the other agents that one agent can perceive, which will conform its neighborhood. Therefore, an explorer may have a large vision

radius, meanwhile a blind agent will have vision radius 0, and will need to receive information about the world.

4.3. Layered architecture for pedestrian navigation

To model the navigation ability of pedestrians from the origin to the destination, and to achieve a specific goal subject to different constraints, it is useful to consider this task as a sequential decision problem following the decomposition principle, which consists to decompose the system to smaller subsystems with high cohesion is each subsystem and loose coupling between subsystems. High cohesion means that the constituted units in the subsystem perform similar tasks and are related to each other. Loose coupling means that changes to one subsystem will not have high impact on other subsystems.

Layering techniques are often used to achieve loose coupling. A layer represents a level of abstraction which only provides services to subsystems of a higher layer. There are many advantages of layering: easy identification of relationships eases the maintenance and the update of systems.

Applied with the layering techniques, our proposed framework consists of four-layer architecture with each layer focusing on some specific functionality, as shown in Fig. 2.1. Each layer focuses on some specific functionality and corresponds to solving a different problem [154]. Fig.4.5. illustrates a common architecture.

The four levels shown correspond to four aspects of crowd simulation:

- ✓ High-level planning: decides where each pedestrian wants to go – his objective.
- ✓ Global planning: determines the plan for reaching the objective, producing a preferred velocity at each time step.
- ✓ Local interaction: tactically adapts the plan to accommodate for unplanned, dynamic obstacles by modifying the preferred velocity, it computes a velocity that deals with local hazards, e.g. to prevent collisions with other agents.
- ✓ Basic behavior: makes the simplest behaviors that a pedestrian can conduct. This layer refers to those pedestrian's behaviors that are not influenced by the presence of other individuals in the environment nearby [155].

The first layer, deciding where each pedestrian wants to go, his objective, belongs to the domain of high-level behavior. The selection of goals can be determined in a number of ways.

The second layer, finding a path to the objective (or goal). It uses the agent's current goal position to compute a geometric route through the environment. For any given start and goal positions, there is typically not a unique path. It is generally accepted that pedestrians seek to achieve the path with the lowest "cost." This cost can refer to distance, travel time, etc. As with the previous layer, this layer is also evaluated infrequently. A path only needs to be generated when the ultimate goal changes, or the environment changes in a way to change the cost of the planned path, rendering the planned path invalid. For a valid path, some point on the path can be used as an immediate goal for an agent – the point toward which the agent should strive at that time step.

The third layer, adapting the plan based on local conditions, is typically the core of the pedestrian model. This level is also referred to as "local interaction". It describes short and medium-range influence of nearby walkers on a generic representative individual. It take into account the visual field of pedestrians and their sensory region, namely, a subset of the visual field where the presence of other people actually affects the walking dynamics.

Basically, the fourth layer consists to compute individual motion for a virtual pedestrian, it describes how agents turn and move when transforming the global and local movement decisions into actual motion. This incorporates agent traits like minimum and maximum values for speed, turn rate, acceleration and deceleration, whether the agent can move backwards or sideways, and how it is oriented in space. The motion should be physically accurate and consistent with the trajectory the pedestrian is traveling [155].

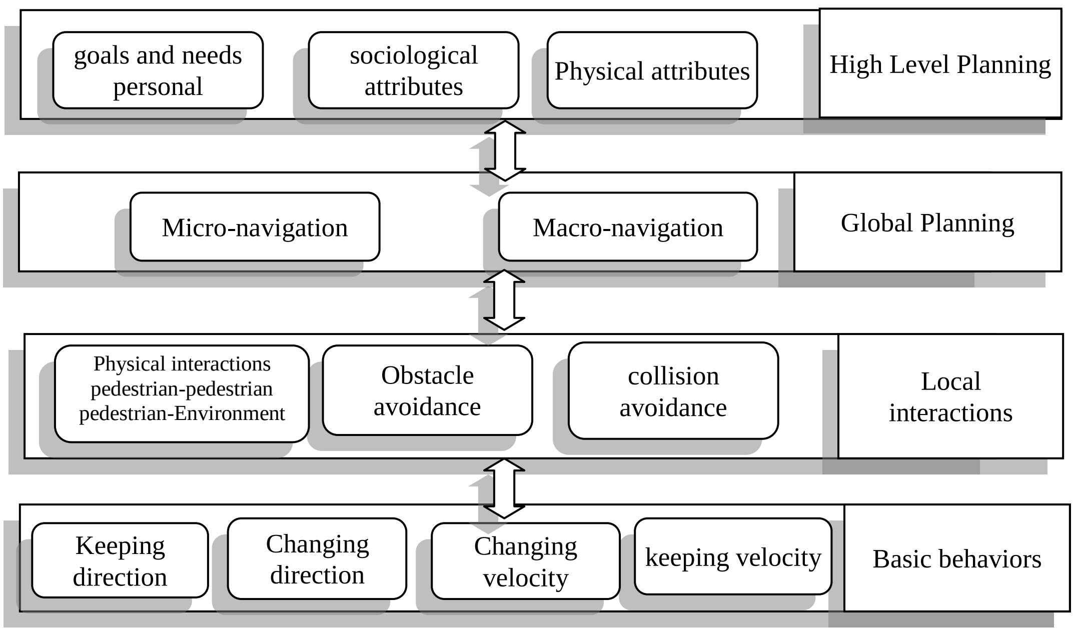


Figure 4. 5 Hierarchical model for pedestrian behaviors

These layers of abstraction communicate at their interfaces. The output of one layer serves as the input to the next layer down. Typically, the first layer produces a goal position to be used by the second layer. The second layer produces a shortest path as a sequence of intermediate goals. These intermediate goals serve as the basis for a time-dependent function of preferred velocity for each agent – it is a velocity vector pointing to a point on the path with a magnitude equal to the agent's preferred walking speed. This preferred velocity serves as an input to the local navigation algorithm. The third layer provides instantaneous velocity to the final layer, providing sufficient information for the motion generation to update the virtual human's skeleton.

4.3.1. Basic behavior

The basic behavior level consists of a set of pre-defined rules (behaviors), which determine how an agent will act under certain situations. The agent's status, personal parameters and its perception will decide which rule to apply and to what extent. By adopting the steering behaviors, some basic rules (e.g. seek to, stop, avoid and keep distance from) have been established in our model. More complex behavior (e.g. following, grouping and clogging) can be achieved by the combination of the basic rules.

a) Speed calculation

Pedestrians move with an individual speed, taking into account the situation, sex, age, surroundings, and so on. We assume that only conditions in front of the person influence on speed. In this case, the speed is computed as follow:

$$\vec{v}_i(t+1) = \vec{v}_i(t) + a(t) * \Delta t \qquad (4.1)$$

$$a(t) = \sum_w \vec{f}_w + \sum_j \vec{f}_j \qquad (4.2)$$

$\vec{f}_w$ means the interaction with the obstacle and $\vec{f}_j$ stands for the virtual force among individuals.

In accordance with the concept of social force model, this behavior reflects the pedestrian's willingness to achieve the desired velocity. At a fixed time t, the pedestrian P_i is at the position $x_i(t)$, and moves with velocity $\vec{v}_i(t)$. This velocity is limited by a maximum speed u_i^{max}, i.e., $\|v_i(t)\| \leq u_i^{max}$.

If not disturbed, this pedestrian will walk into the desired direction $\vec{e}_i(t)$ with certainly desired velocity $\vec{v}_i^{des}(t)$. A deviation between the actual velocity $\vec{v}_i(t)$ and the desired speed $\vec{v}_i^{des}(t)$ due to fluctuation can be modified by relaxation time Δt.

$$\frac{d\vec{v}_i(t)}{dt} = \frac{v_i^{des}(t)\vec{e}_i(t) - \vec{v}_i(t)}{\Delta t} \qquad (4.3)$$

$$\vec{v}_i(t+1) = \vec{v}_i(t) + \frac{d\vec{v}_i(t)}{dt} \qquad (4.4)$$

Desired velocity presents a desired speed v_i^{des} which manifest as free moving speed without external influence, and a desired direction $\vec{e}_i$. Δt is defined as a characteristic time, i.e., relaxation time, represents the capability of an individual to adjust his/her velocity. The smaller value of τ means the pedestrian is faster to adjust his velocity to desired velocity.

b) Keeping the direction

A given pedestrian has an intention to reach a location area to realize a specific activity. This covers people that had intended to move and do not change their activity. In the simulation of the agents' motion we also need to take their goal vectors into account.

This covers people that had change continuously its current position by keeping its desired direction and its preferable velocity. Generally, a pedestrian dislikes deviating from the direct path and the direction is introduced for the pedestrian who chooses the most direct path. The destination direction is given as,

$$\vec{e}_{desired} = \frac{(P_{des} - P_i)}{\|P_{des} - P_i\|} \qquad (4.5)$$

where P_i and P_{des} are the location of the pedestrian i and the location of the destination of pedestrian i, respectively.

$$P_i(t+1) = P_i(t) + v_i(t)\vec{e}_{desired}(t) \times \Delta t \qquad (4.6)$$

c) Changing the direction

The desired direction is defined by the current position and the goal position in the environment, toward which pedestrians desire to move. However, pedestrians change its desired direction vector dynamically due to the stimulus of surrounding environment.

The desired direction is determined by choosing a g_{new} as the objective of detour, and it is given as

$$\vec{e}_{new} = \frac{\left(P_{goal_{new}} - P_{pedestrian}\right)}{\left\|P_{goal_{new}} - P_{pedestrian}\right\|} \qquad (4.7)$$

where P_i and $P_{goal_{new}}$ are the location of the pedestrian i and the location of the new destination g_{new} of pedestrian i, respectively.

4.3.2. Pedestrian Interactions

Pedestrians interact with each other and with the environment around them while walking. These interactions play an important role in the study of their walking behavior. Pedestrians observe the environment when performing the task of walking.

That is, each pedestrian is assumed to interact with those pedestrians in her scanning area and therefore will check on them and their movement. The scanning area is an ellipse which is larger in front of the pedestrian and smaller in the sides. However, the size of the scanning area changes depending on the traffic condition and density. Naturally, there is a strong cooperation between pedestrians that makes walking feasible. A single pedestrian faces several decision situations while walking. Even though these decisions are strongly related in reality, each of them can separately be associated to a behavioral mode.

In pedestrian crowds, one may distinguish at least three different types of interactions:

- ✓ Obstacle avoidance. This behavior gives an agent the ability to maneuver in the virtual environment without colliding with obstacles or other agents. Its implementation is achieved by monitoring an agent's sensory input and reacting to possible collisions. For example, if an agent detects obstacles both in front and on the right but not on the left, then it steers toward the left.
- ✓ Collision avoidance is the basic and most common interaction among pedestrians. It describes the strategic adaptation of walking speed and direction to avoid an upcoming collision with another person. Collision avoidance is at the origin of the lane formation phenomenon in bidirectional flows, and also gives rise to stop-and-go waves in unidirectional flows at intermediate density.
- ✓ Physical interaction takes place when people are in physical contact with one another, at high density levels. Unlike collision avoidance that is based on intentional navigation strategies driven by visual information, physical interaction results in unintentional movements based on pushing and physical pressures exerted among

densely packed people. Physical interaction is typically involved in the emergence of crowd turbulence.

a) Obstacle avoidance behavior

Velocity Obstacles (VO) [48] is a well defined and simple technique that has been widely used for safely navigating agents among static obstacles. VO represents a set of agent velocities that would result in a collision with an obstacle that moves at a certain velocity, at some future time.

Each agent is represented by a radius and a velocity vector. During the planning phase of each step, the following steps are performed for each agent:

1) The current agent's radius is reduced to a point
2) Each of the other agents radii in the scene are increased by the value of the current agent's radius.
3) A velocity obstacle shape is created for each of the other agents in the scene. This is done by taking the position of the current agent and finding a point on the circle created by the other agent's position and its increased radius that creates a line that is tangent to the circle created at the other agent's position. There are two tangent lines from this point to that circle. Both of these tangents make up the velocity obstacle shape.
4) Transform the Velocity Obstacle from step 3 in space by the velocity of the other agent.
5) Choose a velocity that is outside of the Velocity Obstacle created from step 4.

b) Collision avoidance behavior

One of the fundamental problems needed to be handled in crowd simulation is how agents solve collision with both dynamic obstacles. The underlying base simulation of our algorithm is the Reciprocal Velocity Obstacles, or RVO, algorithm presented in [22]. RVO is a traditional rule based algorithm that uses a series of rules to navigate an agent within a crowd.

RVO [22] performs local collision avoidance by computing a space of collision-free velocities for an agent with respect to a number of neighboring agents. The ith agent, A_i, computes a half plane for each of its neighboring agents, A_j, (and a symmetric half plane for agent A_j with respect to agent A_i.)

This algorithm is then applied to each of the other objects and agents in the scene. The union of all of the velocity obstacles is then computed. It is the set of final vectors that could result in a collision. Once that final set of velocities has been determined, collision free movement can be guaranteed by choosing a velocity outside of that velocity obstacle.

4.3.3. Global planning level

The navigation behavior is a cognitive process that is required to successfully guide the virtual pedestrians from a source to a destination where they want to go. Usually, it should be able to find the optimal paths to destinations, which are dependent upon distance, time, or some other criterion such as simplicity or avoid passing congested zones. These algorithms will depend on the context, situation type, etc.

The navigation process consists of two stages: finding a sequence of nodes that efficiently connects the source and destination (Macro-navigation); finding the shortest path through each nodes (Micro-navigation).

a) Macro-navigation

The task of macro-level navigation model consists to given the answer to "how to move from a region to another in the indoor environment". Navigation approaches base on network topology models describing connectivity and adjacency between interior spaces such as rooms and hallways.

In this level, the connectivity graph is used to plan a rough path to reach a specific target in a complex environment. This generates an efficient sequence of intermediate nodes connecting the source and destination.

- ✓ Firstly: Identify the nodes to which the starting location and the final destination belong are.
- ✓ Secondly, a certain optimal routing algorithm (e.g. shortest, fastest or safest) is used to determine which nodes pedestrians will traverse in current circumstance. With each graph's edge weight set to the distance between adjacent decision points, the node sequence is determined by applying A-star as a shortest-path graph search algorithm.

b) Micro-navigation

After specifying the zones which should be accessed, the routing in a zone can start. When a pedestrian arrives at the door attached to the next zones, the navigation route is computed and provided. There are several steps to acquire the route:

- ✓ Step 1: determine the start cell and the target cell in this zone. After that, detect visibility between them.
- ✓ Step 2: if the two cell are mutually visible, then go to the next cell; if it is not, go to step3;
- ✓ Step 3: use a shortest path algorithm to find out the shortest path between the start and target cells.

5. Conclusion

We have adopted an agent-based approach to the modeling of pedestrians and proposed a hierarchical navigation model based on observations about real pedestrians.

The building space of simulation environment was represented by using two spatial representations, fine graph used to model detailed interaction between agents, and the coarse graph approach used to provide the connectivity between the components of the environment.

The pedestrian behaviors in the model were implemented by layered framework, each layer is responsible for a different stage of the process, and has to communicate with the others. This framework is generic and flexible to employ different implementations within each module for different simulation purposes and scenario requirements. The modular approach ensures that the changes in one module will have minimum effects on other modules.

Moreover, various physical, psychological and behavioral factors have been introduced to agents to explicitly and naturally reproduce pedestrian behaviors for different environments.

Chapter 5: Continuum model for crowd dynamic modeling

1. Introduction

Crowds are ubiquitous in the real world, and simulating their motion is a crucial problem in computer graphics and animation since the crowds of people exhibit behavior of enormous complexity and subtlety. A crowd model must not only include individual human motion and environmental constraints such as boundaries, but also address a bewildering array of dynamic interactions between people. Further, the model must reflect intelligent path planning through this changing environment. Humans constantly adjust their paths to reflect congestion and other dynamic factors.

Virtually all previous work in the graphics and crowds literature has been agent-based. In agent-based approaches, every single agent has its own computation of future behavior. Path planning and collision avoidance is performed for each agent in the scene. This approach is the most natural one since it is the way that real crowds work: each human makes his own motion decisions according to only the information he has, such as visibility, information about the destination, and proximity. However, this approach has the disadvantage that when simulating very dense crowds, it requires large computational time.

Here, I focus specifically on the problem of simulating the dynamics of large, dense crowds in real time. Such crowds exhibit a low interpersonal distance and a corresponding loss of individual freedom of motion. This observation suggests that the behavior of such crowds may be modeled efficiently on a coarser level, treating its motion as the flow of a single aggregate system.

This chapter presents a real-time motion synthesis model for simulating large and dense crowds. We view crowds as fluids, and adopt fluid dynamic on the system. This formulation yields a set of dynamic density and velocity fields that represent the crowd distribution and guide all individual motion simultaneously. Our approach unifies global navigation, congestion avoidance, environment interactions and other specific cases into optimal equations of fluid dynamic. Global path planning is pre-computed and constant before environment changes. The status of crowd flow is recorded in the coarse grid without computing or updating most of the individuals.

Locally, the motion of each individual in sight is driven by a simple equation considering interactions with his neighbors.

2. Continuum model principles

In this section we develop a mathematical model of crowd dynamics. We begin with a set of observations about crowd flow. Crowd behaviors are consistent at the macro with many of the characteristics of fluid dynamics found, such as flowing from high density region to low density region, pressure being interrelated to the density of the fluid, convective acceleration caused by a (possibly steady) change in velocity over position, acceleration caused by external forces, etc.

The foundation of our continuum model is three principles. The first one is common for all continuum pedestrian flow models. It consists of a conservation law and the continuum assumption. The second principle consists of defining the environment constraints that affect the common behavior of pedestrians and their interactions. The third principle relates to path choice strategy of pedestrians.

They form the basis of our continuum modeling approach. The principles are as follows:

- ✓ ***Principle 1:*** assumes that pedestrians can be aggregated and that the traffic state can be described by aggregate continuum variables such as density, flow and average velocity. Principle 1 is the single undisputed principle in pedestrian flow modeling. It states that pedestrians are conserved. This means that pedestrians can only enter the system through inflow at the boundaries and that they only leave the system through outflow at the boundaries. Pedestrians are not created in the system itself, nor do they disappear. To the best of our knowledge, this principle is included in all traffic flow models.
- ✓ ***Principle 2.*** Pedestrian movement is determined by a field that affects their walking direction and speed. Every considered aspect (like the planned path to a target, obstacles like walls or other pedestrians, and so on) has an effect on the environment of the pedestrians generating an interaction field of distant forces. The data described by this field can be represented by partial differential equations (PDEs).

- ✓ ***Principle 3.*** The heuristics that apply in pedestrian traffic should be sufficiently simple in order to be accessible by the majority of pedestrians. If several simple strategies are considered, the one that proves most effective is likely to be preferred since pedestrians are supposed to seek efficiency, too.

3. Macroscopic Modeling framework

Our proposed macroscopic model is based on a set of pedestrian-specific coupled partial differential equations. The dynamics of crowd obey the mass conservation principle, the basis of our proposed model is the flow conservation equation which describes the dynamic evolution of pedestrian density.

We adopt a path choice strategy, in which the walking direction of pedestrian is genuinely modeled by accounting two basic contributions: on the one hand, the desire to follow the shortest path to a specific destination; on the other hand, the necessity of avoiding overcrowded areas.

Pedestrians moving from one direction to the other, adapt their velocity to the new local perceived density conditions, namely they decrease speed for increasing perceived density and increase it for decreasing perceived density.

3.1. Macroscopic Pedestrian Characteristics

The macroscopic characteristics concern about a group or a crowd of pedestrians rather than individuals. Macroscopic characteristics can describe the overall motion features of a crowd from different aspects such as the flow rate, dominant direction, and the transitions of different motion patterns over time for the whole crowd.

In this thesis, fundamental characteristics of pedestrian crowd are flow, speed and density. These characteristics can be observed and studied at the macroscopic levels. Macroscopic study may be selected for high density, large scale systems in which the behavior of groups of unit is sufficient.

3.1.1. Average moving speed

is an important parameter of pedestrian movement. Relevant studies may help calibrate the proposed model since individual pedestrian's speed will be influenced by the average moving speed of a crowd under certain situation (e.g., in a dense crowd). Several studies have attempted to describe the average moving speed of pedestrians depending on various factors such as the physical ability, social position (in a crowd) and the crowd density.

There are two common ways to compute the average or mean speed, which is called time mean speed and space mean speed. The time mean speed is the average speed of all pedestrian passing a line on the pedestrian trap over a specified period of time and it is calculated as an arithmetic average of the spot speed or instantaneous speed, that is

$$\tilde{v}(t) = \frac{\sum_{i=1}^{N} v_i(t)}{N} \qquad (5.1)$$

where N is the number of observed pedestrian and v_i is the instantaneous speed of the i^{th} pedestrian. The time mean speed, $\tilde{v}$, is taken as an average value over specified duration of time corresponding to the observation of flow, density, space mean speed and other characteristics (e.g. every 5 minutes of observation). If the walking distance of all individual pedestrians, ω_i, during fixed observation periods T can be gathered, the time mean speed can be also be calculated using

$$\tilde{v} = \frac{\sum_{i=1}^{N} \omega_i}{N \cdot T} \qquad (5.2)$$

The space mean speed is the average speed of all pedestrian occupying the pedestrian trap over a specified time period and calculated based on the average travel time for the pedestrian to traverse a fixed length of a pedestrian trap, L . If t_i^{out} and t_i^{in} represent time of pedestrian i^{th} to go out and go in the pedestrian trap, the space mean speed, u, is calculated as

$$u = \frac{L}{\tilde{t}} \qquad (5.3)$$

Where the denominator is the average travel time

$$\tilde{t} = \frac{\sum_{i=1}^{N}\left(t_i^{out} - t_i^{in}\right)}{N} \qquad (5.4)$$

3.1.2. Crowd density

Crowd density is one of the other factors affecting human movement and behavior, particularly in a complex scenario where a large number of people is involved.

Crowd density refers to the number of people per square meter for a stationary or moving crowd. Pedestrian density increases (i.e. interpersonal distances lessen) around particularly attractive places, and it decreases with growing velocity variance.

In order to determine the density, in general a rectangular area is defined and the number of pedestrians within this area is counted. The instantaneous density at time t is given by

$$\rho(t) = \frac{N}{|A|} \qquad (5.5)$$

with N the number of pedestrian at the moment t that reside within the measurement area A. $\rho(t)$ can be averaged over a time period Δt as follows:

$$\langle\rho\rangle_{\Delta t} = \frac{1}{\Delta t}\int_{\Delta t} \rho(t)\,dt \qquad (5.6)$$

3.1.3. Pedestrian flow rate

Pedestrian flow rate denoted by q is a result of a movement of many individuals. Pedestrian flow rate or volume is defined as the number of pedestrian that pass a perpendicular line of sight across a unit width of a walkway during a specified period of time and normally has a unit of ped/min/m (number of pedestrian per minutes per meter width). Pedestrian volume is useful for examining the trend and planning facilities, evaluating safety and level of service. If w and L denote the width and length of the pedestrian trap respectively, and N indicates the number of pedestrians observed during the observation time T , then the flow rate can be calculated as

$$q = \frac{N}{T \cdot w} \qquad (5.7)$$

Reciprocals of these variables have different physical interpretations and can also be used to represent traffic states. Reciprocal variables are summarized in Table 5.1.

Table 5.1 Definition of physical variables

Variable	Reciprocal	Measurement
Spacing	Reciprocal of density	Average distance between two successive pedestrians
Headway	Reciprocal of flow	Average time between two successive pedestrians passing a fixed point
Pacing	Reciprocal of speed	Time spent per unit length of road

3.2. Conservation Law

The models for traffic, whether they are one-equation or system of equations, are based on the physical principle of conservation. When physical quantities remain the same during some process, these quantities are said to be conserved.

Putting this principle into a mathematical representation will make it possible to predict the densities and velocities patterns at future time.

In our case, the number of pedestrian in a specific section $[x_1, x_2]$ is our physical quantities, and the process is to keep it fixed (i.e., the number of pedestrians coming in equals the number of pedestrians going out of the segment).

Considering pedestrians are moving from left to right of the section as show in Fig.5.1. The number of pedestrians within $[x_1, x_2]$ at a given time t is the integral of the crowd density given by

$$N = \int_{x_1}^{x_2} \rho(x,t)\, dx \qquad (5.8)$$

In the above equation, it is implied that the number of people within $[x_1, x_2]$ is at maximum when crowd density is equal to jam density ρ_m which is associated with the maximum number of pedestrians that could possibly fit in a unit area.

The number of pedestrians can still change (increase or decrease) in time due to pedestrian crossing both ends of the section. Assuming no pedestrians are created or destroyed, then the change of the number of pedestrians is due to the change at the boundaries only. Therefore, the rate of change of the number of pedestrians is given by

$$\frac{dN}{dt} = f_{in}(\rho, v) - f_{out}(\rho, v) \qquad (5.9)$$

since the number of pedestrians per unit time is the flow $f(\rho, v)$.

Combining (8), and (9), yields the integral conservation law

$$\frac{d}{dt}\int_{x_1}^{x_2} \rho(x,t)dx = f_{in}(\rho, v) - f_{out}(\rho, v) \qquad (5.10)$$

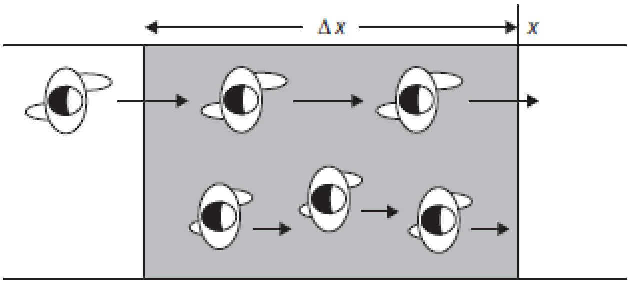


Figure 5. 1 One-dimension Flow

This equation represents the fact that change in number of entities is due to the flows at the boundaries. Now let the end points be independent variables (not fixed with time), then the full derivative is replaced by partial derivative to get

$$\frac{\partial}{\partial t}\int_{x_1}^{x_2} \rho(x,t)dx = f_{in}(\rho,v) - f_{out}(\rho,v) \qquad (5.11)$$

The change in the number of pedestrians with respect to distance is given by

$$f_{in}(\rho,v) - f_{out}(\rho,v) = -\int_{x_1}^{x_2} \frac{\partial f}{\partial x}(\rho,v)dx \qquad (5.12)$$

and by setting the last two equations equal to each other, we get

$$\int_{x_1}^{x_2} \left[\frac{\partial \rho}{\partial t}(x,t) + \frac{\partial f}{\partial x}(\rho,v)\right] dx = 0 \qquad (5.13)$$

This equation states that the definite integral of some quantity is always zero for all values of the independent varying limits of the integral. The only function with this feature is the zero function. Therefore, assuming $\rho(x,t)$, and $q(x,t)$ are both smooth, the conservation law is found to be

$$\rho_t + f_x(\rho,v) = 0 \qquad (5.14)$$

We need to mention that this equation is valid for pedestrian flow and many more physical quantities.

3.3. Flow

In this section, we will illustrate the close relationship between the three variables: density, velocity and traffic flow. Suppose there is a crossing section with pedestrians moving with constant velocity v_0, and constant density ρ_0 such that the distance between the pedestrians is also constant as shown in the Fig.5.2 (a).

Now let an observer measure the number of pedestrians per unit time τ that pass him (i.e. traffic flow f). In τ time, each car has moved $v_0\tau$ distance, and hence the number of pedestrians that pass the observer in τ time is the number of pedestrians in $v_0\tau$ distance, see Fig.5.2 (b).

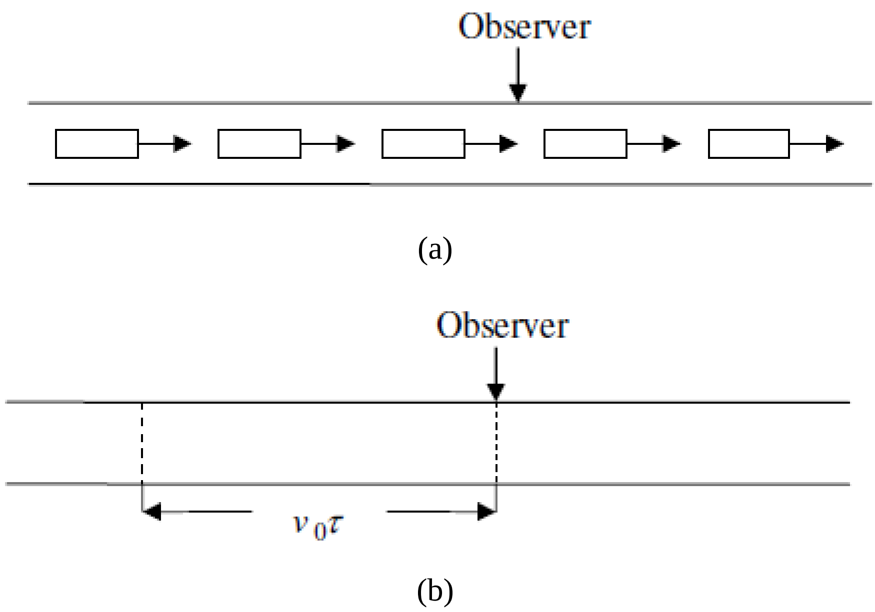


Figure 5. 2 (a) Constant flow of pedestrians, (b) Distance traveled in τ hours for a single pedestrian.

Since the density $\rho_0$is the number of pedestrians per unit area and there is $v_0\tau$ distance, then the pedestrians flow is given by

$$f = \rho_0 v_0 \qquad (5.15)$$

This is the same equation as in the time varying case, i.e.,

$$f(\rho, v) = \rho(x,t)v(x,t) \qquad (5.16)$$

To show this, consider the number of pedestrians that pass point $x = x_0$ in a very small time Δt. In this period of time the cars have not moved far and hence $v(x,t)$, and $\rho(x,t)$ can be approximated by their constant values at $x = x_0$ and $t = t_0$. Then, the number of pedestrians passing the observer occupy a short distance, and they are approximately equal to $\rho(x,t)v(x,t)\Delta t$, where the traffic flow is given by (5.16).

$F(\rho, x, y, t) = (f_1(\rho, x, y, t), f_2(\rho, x, y, t))$ $(ped/(m \cdot s^{-1}))$ is the flow vector and f_1, f_2 represent the flow in x- and y directions, respectively; denotes a 2D continuous walking facility; T (s) is the time horizon of analysis. Flow intensity or the flow-density relationship, $\|\mathrm{F}(\rho, \mathrm{x}, \mathrm{y}, \mathrm{t})\|$, is defined as

$$\|\mathrm{F}(\rho, \mathrm{x}, \mathrm{y}, \mathrm{t})\| = \sqrt{\mathrm{f}_1^2(\rho, \mathrm{x}, \mathrm{y}, \mathrm{t}) + \mathrm{f}_2^2(\rho, \mathrm{x}, \mathrm{y}, \mathrm{t})}$$

3.4. Desired direction of motion

We now proceed to describe how the path choice strategy is specified. The paths chosen by pedestrians are considered to be the consequence of a series of potentially complicated decision making processes undertaken by pedestrians in determining how to travel from the origin (x, y) to their goal, based on the information available.

In practice, people find and travel the actual minimum distance path to their destination. However, this preference is tempered by a desire to avoid congestion and other time-consuming situations. This can be seen as the classic trade-off between energy and time minimization. Additionally, people prefer to minimize their exposure to areas of high “discomfort.”

At this step we describe a path choice strategy by defining $\mathrm{C}(\mathrm{x}, \mathrm{y}, \mathrm{t})$ (in s/m) as the local walking cost per unit distance of movement at location (x, y) and time t. Here C is computed in a similar manner as that proposed by Treuille et al. [28], based on an instantaneous equilibrium travel cost.

The cost distribution $\mathrm{C}(\mathrm{x}, \mathrm{y}, \mathrm{t})$ is thus defined as to minimize a linear combination of the following three terms:

- ✓ ***Distance.*** Distance is a common factor used by pedestrians when making a path choice strategy and is the primary heuristic in many search based strategies. Pedestrians will choose the route with the shortest distance.
- ✓ ***Time***. Time is another factor that affects the path choice strategy. A person must choose the shortest path that takes less time
- ✓ The discomfort felt, per unit time, along the path.

Mathematically, the three hypothesis mean that, given the set Π of all paths from a person’s location x to some point in the fixed goal G, that person must choose the path $\mathrm{P} \in \Pi$ that minimizes

$$\mathrm{C_p} = \mathrm{W_L}\int_{\mathrm{p}} 1\ \mathrm{ds} + \mathrm{W_T}\int_{\mathrm{p}} 1\ \mathrm{dt} + \mathrm{W_D}\int_{\mathrm{p}} \mathrm{Discomfort}\ \ \mathrm{dt}$$

$$= \mathrm{W_L}\int_{\mathrm{p}} 1\ \mathrm{ds} + \mathrm{W_T}\int_{\mathrm{p}} \frac{1}{v(t)}\ \mathrm{ds} + \mathrm{W_D}\int_{\mathrm{p}} \frac{\mathrm{Discomfort}}{v(t)}\ \ \mathrm{ds}$$

by $\mathrm{dt} = \frac{\mathrm{ds}}{v(t)}$, then

$$\mathrm{C_p} = \int \frac{v(t)\cdot \mathrm{W_L} \ + \mathrm{W_T} \ + \ \mathrm{W_D} \cdot \mathrm{Discomfort}}{v(t)}\ \mathrm{ds} \qquad (5.17)$$

where the $\mathrm{W}_{\{\mathrm{L,T,D}\}}$ are the length, time and discomfort weight respectively.

These weights can be set by the user. P is the path, and Discomfort is the discomfort suffered on the path, while Speed is the speed greater than zero that the agent achieves along the path. An integral with ds means that it is taken with respect to the path length, and dt indicates the same for the time spent on the path. According to the requirements an agent will pick the path that minimizes this function.

3.5. Optimal Path Computation

We now show how potential functions can be used to find optimal paths given the path cost described in equation (5.17).

A generalized cost potential function $\phi(\mathrm{x,y,t})$ is introduced over the scene such that the potential function, at a specific location x, represents the cost of reaching the goal through the optimal path.

Intuitively, at any location, a person should move in the negative direction of the gradient of this function, as this will decrease cost of the path most rapidly.

The potential function e ϕ satisfies the eikonal equation:

$$\|\nabla\phi(x,y,t)\| = C_p \qquad (5.18)$$

The potential field ϕ is assigned with the value of 0 inside a goal, and the other grid cell values are approximated by solving a finite difference approximation to the above equation outwards from the goal position.

3.6. Desired direction

Finally, we compute the vector field which defines the movement direction. Following the works of Hughes [98], we assume that the pedestrians movement is opposite to the gradient of a scalar potential ϕ, that is

$$\vec{\mu} = -\frac{\nabla\phi}{\|\nabla\phi\|} \qquad (5.19)$$

where the potential ϕ corresponds to an instantaneous travel cost which pedestrians want to minimize and is determined by the eikonal equation (5.18).

3.7. Speed

The function $V(t)$ characterizes how the speed of pedestrians changes with density. Maximum permissible speed is a density-dependent term. Various speed-density relations are available in the literature.

At low densities, agents should move freely at the maximum speed possible. As indicated in Continuum Crowds, the maximum speed allowed could depend on the topography of the terrain. As an example, agents could slow down when moving up a slope. Whereas at high densities the agents should slow down, therefore density constraints are applied, the speed is dominated by the movement of the nearby people, preventing an agent from trying to move in the opposite direction of the movement in a very dense region. At medium densities, the speed is computed by interpolation. This definition of permissible speed supports lane formation between the agents moving in the same direction.

We assume that the pedestrian speed $v(x,t)$ depends on the pedestrian density

$$v(x,t) = V(x,\rho(x,t))$$

where $V(x,\rho(x,t))$ is the function of the pedestrian speed with respect to the density and location dependence.

The speed function $V(x,\rho(x,t)) : [0,\rho_{max}] \rightarrow R^{+}$ is assumed to be decreasing. For our simulations we choose the exponential dependence

$$V\big(x,\rho(x,t)\big) = v_{max}\, e^{-\alpha\left(\frac{\rho}{\rho_{max}}\right)^2} \qquad (5.20)$$

where v_{max} is the free flow speed, ρ_{max} is the congestion density and α is a positive constant.

4. Numerical approach

The development of numerical schemes for the solutions of the systems (5.14), (5.17) and (5.18) is dealt with in this present section by using some first order accurate methods.

4.1. Numerical procedure

The solution space (x, y) is divided into $I \times J$ non-overlapping control volumes constructing an uniform grid.

Here, $I_{ij} = I_i \times I_j$, $I_i = [x_{i-\frac{1}{2}}, x_{i+\frac{1}{2}}]$ and $I_j = [y_{j-\frac{1}{2}}, y_{j+\frac{1}{2}}]$. The centers of I_i and I_j are denoted by $x_i = \frac{1}{2}\left(x_{i-\frac{1}{2}} + x_{i+\frac{1}{2}}\right)$ and $y_j = \frac{1}{2}\left(y_{j-\frac{1}{2}} + y_{j+\frac{1}{2}}\right)$, respectively, and let Δx and Δy two constant steps for space

$$\Delta x = x_{i+1} - x_i, \Delta y = y_{j+1} - y_j$$

The approximations of the density $\rho(x, y, t)$ and cost potential $\phi(x, y, t)$ are stored at the centers of the control volumes.

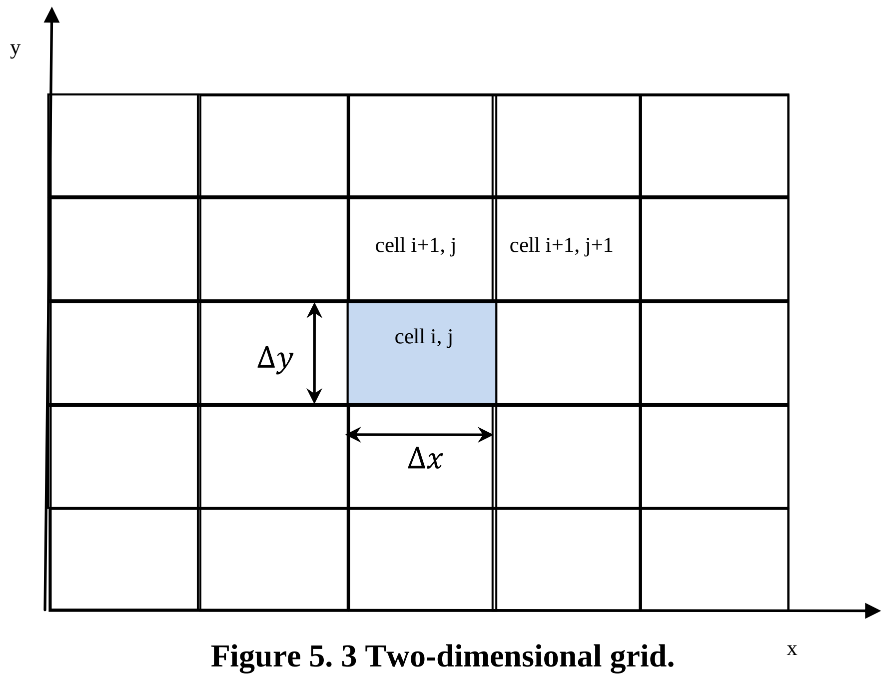


Figure 5. 3 Two-dimensional grid.

4.2. Numerical methods for hyperbolic conservation laws and traffic flow

In this section we focus our attention on numerical methods to approximate hyperbolic conservation laws. Usually each mathematical model needs an individual numerical treatment in order to reflect all its physical features.

When an equation cannot be solved, we can use a variety of numerical methods such as

- ✓ Finite elements
- ✓ Finite volumes
- ✓ Finite differences

For conservation laws, finite differences are often used. These aim to construct an approximate solution ρ^{n+1} at time $n+1$ from previous solutions ρ^{n}, ρ^{n-1} etc depending on the level of the scheme.

In this subsection, we assume that the total perceived instantaneous travel cost $\phi(x, y, t)$ is known for all (x, y) and time t. The semi-discrete version of the first-order cell-centered FV scheme for Eq. (5.14) can be defined as

$$\frac{d\rho_{ij}}{dt}+\frac{(\hat{f}_1)_{i+\frac{1}{2}j}-(\hat{f}_1)_{i-\frac{1}{2}j}}{h}+\frac{(\hat{f}_2)_{i\,j+\frac{1}{2}}-(\hat{f}_1)_{i\,j-\frac{1}{2}}}{h}=0 \qquad (5.21)$$

Here, h is the mesh size in both dimensions for simplicity and $\hat{f}_1$, $\hat{f}_2$ are the numerical fluxes across each volume interface which are calculated by the following Lax-Friedrichs scheme.

$$(\hat{f}_1)_{i+\frac{1}{2}j}=\frac{1}{2}\left[(f_1)_{i+1\,j}+(f_1)_{i\,j}-\alpha_x\left(\rho_{i+1j}-\rho_{ij}\right)\right]$$

$$(\hat{f}_2)_{i\,j+\frac{1}{2}}=\frac{1}{2}\left[(f_2)_{i\,j+1}+(f_2)_{i\,j}-\alpha_y\left(\rho_{i\,j+1}-\rho_{ij}\right)\right]$$

where $\alpha_x=\max_{1\le i\le J}\left(U\frac{|\phi_x|}{\|\nabla\phi\|}\right)_{ij}$, and $\alpha_y=\max_{1\le j\le J}\left(U\frac{|\phi_y|}{\|\nabla\phi\|}\right)_{ij}$

4.3. Fast sweeping method for Eikonal equation

The Eikonal equation is of significant interest in the field of numerical analysis. Many numerical methods have been proposed to solve the Eikonal equation. The most stable methods among those are the fast marching method and the fast sweeping method.

The fast sweeping method [97, 94] is an iterative algorithm with optimal complexity that finds the numerical solution by using the non linear upwind method and Gauss-seidel type iterations with alternating sweepings in predetermined directions.

Therefore, we chose the fast sweeping method (FSM), which is based on the third-order WENO scheme for its lower complexity.

The fast sweeping WENO method starts with the following initialization.

Step 1: Initial guess: if (x_i, y_j) is a goal, then $\phi_{ij} = 0$ otherwise $\phi_{ij} = \infty$

Step 2: The following Gauss–Seidel iterations with four alternating direction sweepings are then performed.

(1) $i = 1{:}\ I,\ \ j = 1{:}\ J$; (2) $i = 1{:}\ I,\ \ j = J{:}\,1$;

(3) $i = I : 1,\ j = 1{:}\ J$; (4) $i = I{:}\ \ 1,\ \ j = J{:}\,1$;

where (i, j) is the grid index pair in (x, y) and I and J are the number of grid points in x and y, respectively. When we loop to a point (i, j), the solution is updated as follows:

$$\phi_{i\,j}^{new} = \begin{cases} \min\left(\phi_{i\,j}^{x\,min}, \phi_{i\,j}^{y\,min}\right) + c_{ij}\,h, & if\ \left|\phi_{i\,j}^{x\,min} - \phi_{i\,j}^{y\,min}\right| \le c_{ij}\,h \\ \dfrac{\phi_{i\,j}^{x\,min} + \phi_{i\,j}^{y\,min} + \left(2c_{ij}^2 h^2 - \left(\phi_{i\,j}^{x\,min} - \phi_{i\,j}^{y\,min}\right)^2\right)^{\frac{1}{2}}}{2} & otherwise \end{cases}$$

where $c_{ij} = C(x_i, y_j, t)$, and

$$\begin{cases} \phi_{i\,j}^{x\,min} = \min\left(\phi_{ij}^{old} - h(\phi_x)_{ij}^{-}, \phi_{ij}^{old} - h(\phi_x)_{ij}^{+}\right) \\ \phi_{i\,j}^{y\,min} = \min\left(\phi_{ij}^{old} - h\left(\phi_y\right)_{ij}^{-}, \phi_{ij}^{old} - h\left(\phi_y\right)_{ij}^{+}\right) \end{cases}$$

with

$$(\phi_x)_{ij}^{-} = (1 - w_-)\left(\frac{\phi_{i+1\,j} - \phi_{i-1\,j}}{2h}\right) + w_-\left(\frac{3\phi_{i\,j} - 4\phi_{i-1\,j} + \phi_{i-2\,j}}{2h}\right)$$

$$(\phi_x)_{ij}^{+} = (1 - w_+)\left(\frac{\phi_{i+1\,j} - \phi_{i-1\,j}}{2h}\right) + w_+\left(\frac{3\phi_{i\,j} - 4\phi_{i-1\,j} + \phi_{i-2\,j}}{2h}\right)$$

$$w_- = \frac{1}{1 + 2r_-^2}, \quad r_- = \frac{\varepsilon + \left(\phi_{i\,j} - 2\phi_{i-1\,j} + \phi_{i-2\,j}\right)^2}{\varepsilon + \left(\phi_{i+1\,j} - 2\phi_{i\,j} + \phi_{i-1\,j}\right)^2}$$

$$w_{+}=\frac{1}{1+2r_{+}^{2}},\quad r_{+}=\frac{\varepsilon+\left(\phi_{i\,j}-2\phi_{i+1\,j}+\phi_{i+2\,j}\right)^{2}}{\varepsilon+\left(\phi_{i+1\,j}-2\phi_{i\,j}+\phi_{i-1\,j}\right)^{2}}$$

The definitions for $\left(\phi_y\right)_{i\,j}^{-}$ and $\left(\phi_y\right)_{i\,j}^{+}$ are of course analogous.

Convergence is declared if

$$\|\phi^{new}-\phi^{old}\|\leq\delta$$

where δ is a given convergence threshold value. We use $\delta=10^{-9}$ in our computation. The algorithm converges very rapidly in our numerical simulation.

4.4. Time discretization

Finally, the semi-discrete scheme (5.21) must also be discretized in time. We use the third-order total-variation-diminishing (TVD) Runge-Kutta method, which is the convex combination of three Euler forward time discretization steps and can maintain the stability of the spatial discretization [106].

$$\begin{cases}\rho^{(1)}=\rho^{n}+\Delta t L(\rho^{n})\\ \rho^{(2)}=\dfrac{3}{4}\rho^{n}+\dfrac{1}{4}\left(\rho^{(1)}+\Delta t L\left(\rho^{(1)}\right)\right)\\ \rho^{n+1}=\dfrac{1}{3}\rho^{n}+\dfrac{2}{3}\left(\rho^{(2)}+\Delta t L\left(\rho^{(2)}\right)\right)\end{cases}$$

where

$$L(\rho)=\frac{(\hat{f}_1)_{i+\frac{1}{2}\,j}-(\hat{f}_1)_{i-\frac{1}{2}\,j}}{h}+\frac{(\hat{f}_2)_{i\,j+\frac{1}{2}}-(\hat{f}_2)_{i\,j-\frac{1}{2}}}{h}.$$

Here, the time step Δt needs to satisfy the Courant-Friedrichs-Lewy (CFL) condition. We take the CFL coefficient to be 0.1 in our computation.

4.5. Solution procedure

The main time evolution equation to be solved is Eq. (5.14). When the flux function f is known, this is a scalar two-dimensional hyperbolic conservation law. We use the fifth-order finite difference WENO scheme.

In summary, starting from the density ρ^n at time level n, we obtain the density qn+1 by the following steps in an Euler forward time discretization.

1. Obtain the cost function C_p by formula (5.17);

2. Solve the Eikonal equation (18) by a third-order WENO discretization using the fast sweeping method to obtain /;

3. Obtain the magnitude $\|f\|$ of the flux f by using formula (5.16);

4. Obtain the flux f by using formula (5.21); and

5. Use the fifth-order Lax–Friedrichs WENO scheme to obtain ρ^n by solving the conservation law (5.14).

5. Conclusion

We propose a framework to simulate and visualize pedestrian crowds in very dense situations. The proposed crowd animation system simulates the agents with a continuum dynamics-based approach applied to the crowd model of Hughes [98]. During simulation, people are coarsely distributed and show homogeneous behaviors.

The taken continuum-approach is able to simulate a number of agent groups up the resolution of the simulation grid, and the cost per agent is amortized for each group of agents. Thus, the continuum-based approach is more suitable for outdoors emergency simulations, as opposed to the computationally-demanding agent-based approaches.

My approach unifies global path planning and local collision avoidance into a single optimization framework. People in my model do not experience a discrete regime change in the presence of other people. Instead, they perform global planning to avoid both obstacles and other people. This dynamic potential field formulation also guarantees that paths are optimal for the current environment state, so people never get stuck in local minima.

Chapter 6: Hybrid approach for crowd simulation

1. Introduction

Crowd simulation has become an efficient tool to study the behavior and movement pattern of crowd in real life.

From the level of detail point of view, models used for crowd simulation can broadly be categorized in microscopic (high resolution) and macroscopic approaches (low resolution). The microscopic approach focuses on the realism of the behaviors of each individual, thus the perception, the memory, the planning, the psychology and the emotion of every agent are taken into account and each agent could react differently to the same event as a result. The macroscopic, which aims at achieving real time simulation for very large crowds, thus the behavior of each individual is not important as long as the overall crowd movement looks realistic.

Therefore, none of the two approaches is separately able to capture real crowd dynamics. A natural strategy is therefore to combine the different models together, with the aim of obtaining both execution efficiency from macroscopic model and the fine-grain simulation result from microscopic model.

This paper proposes a hybrid model for simulating crowd behaviors and its movements. The main thought of this model is to couple macroscopic and microscopic models within the same framework. Therefore, it is possible to use the advantages of the two models by adapting them to the treated phenomena and situations while minimizing their disadvantages. Issues like environmental and global crowd movement pattern are simulated by macroscopic model. Whereas, the microscopic model only simulates how agent makes decision and moves directed by the simulation result from the macroscopic model.

The simulation environment is partitioned in terms of the crowd characteristic. Each partition is then modeled independently with either a macroscopic or microscopic model. During execution of the simulation, the two types of models work simultaneously on the corresponding partitions.

Our proposed model has the ability to dynamically select and switch to a suitable simulation model at runtime, based on the state of the simulated world. It also defines two types of interaction mechanisms, i.e., Micro-Macro transition and Micro-Macro transition that are required to transfer data at the boundaries between the partitions.

The rest of the chapter is organized as follows: objective and motivation to use hybrid is introduced in Section 2. An overview of the hybrid modeling of crowd simulation, which is composed of environment model and crowd model, is introduced in Section 3. Then the representation of virtual environment and crowd model are discussed in section 4, and 5. The interactions between the different models are defined in Section 6. The chapter is concluded in Section 7.

2. Objective and Motivation

As a collective and highly dynamic social group, a human crowd is a fascinating ubiquitous phenomenon has been observed with interesting biological, social, cultural, and spatial patterns in our everyday life. It forms a living complex system that contains, a great number of interacting individuals moving in the same physical environment, and has the ability to generate a new quality of macroscopic collective behavior the manifestations of which are the spontaneous formation of distinctive temporal, spatial or functional structures.

Real-time simulation of human crowds is highly challenging because pedestrian dynamics exhibits a rich variety of both independent and collective effects, such as lane formations, oscillations at bottlenecks, chemotaxis and panic effects. The core problem of realistic crowd simulation is to build an efficient and accurate behavioral model, that accounts for what real pedestrians do, by simulating the movement of the whole crowd and each agent in crowd.

We believe that, before designing a crowd simulation model for realistic and effective modeling of crowd dynamics and behaviors, there is a need to offer a better understanding of the mechanics behind these daily behaviors as well as reproduce the resulting, fascinating large-scale patterns. Motivated by this requirement, we make the following observations:

- ✓ **Observation 01:** Human behavior is extremely complex and exhibit large variation based on situations and settings. It also depends on individual characteristics such as age, sex, height, and cultural background, to name the few. Human behavior can vary drastically based on the given situation. For instance, transition from walking to panic can be instantaneous given a dangerous situation (e.g. stampede).

- ✓ **Observation 02:** Crowd have the ability to express a strategy. Walkers are capable to develop specific strategies, which depend on their own state and on that of the entities in their surrounding environment. Different strategies can appear in the dynamics. The modeling of pedestrians' strategy should include several features, for instance trend toward the exit or a meeting point, following or avoiding streams and clusters, avoiding overcrowding in the proximity of walls, clustering of individuals with similar activity, avoiding individuals with different activity, and possibly others.
- ✓ **Observation 03:** The pedestrian crowd is a large scale phenomena that can vary from individual people to groups to large crowds and displays many levels of complex behaviors. The dynamics of such systems can be viewed on a wide range of scales: from the chaotic, fluctuating interactions between individual objects on the finest scales, to the coherent aggregate flow of the system on the largest scales. This interplay between the bulk motion and the fine detail in these so-called multi-scale phenomena makes them extremely rich and fascinating from a theoretical as well as a visual perspective.
- ✓ **Observation 04:** The phenomena that was observed in crowd by psychologists is its homogeneous nature. People in the crowd often acting in a coordinated fashion, as if governed by a single mind [4]. However, this coordination is achieved with little or no verbal communications. A phenomenon observed in crowds, and discovered early in crowd behavior research, is that people in crowds act similar to one another, often acting in a seemingly coordinated fashion, as if governed by a single mind. However, this coordination is achieved with little or no verbal communication.
- ✓ **Observation 05:** In reality pedestrian crowds are naturally composed of heterogeneous individuals. Each pedestrian is walking, It has a goal that they want to reach, while avoiding bumping into other people, or tripping on an obstacle. In this cadre, human behavior choice is highly dependent on individual characteristics such as personality, gender, age, and so on. Among them, decision makers' personality traits are crucial sources of difference between individuals, and accounting for personality can make human decision model more natural.

These observations suggest that the fundamental choice of suitable model for crowd simulation leads to several challenges which can be classified along two axes.

The first major problem is that a successful crowd model has the ability to simulate the movements and the behavior patterns of large numbers of pedestrians as realistically as possible in real-time [113]. Most applications require a human crowd simulated in real time, with higher level of detail and an accurate realism of behaviors. Then, there is still a clear relationship between the accuracy realism of crowd behaviors and the computational costs of simulation.

Satisfying these both constraints at the same time is particularly a challenge of great importance. The majority of the previous models have a limited ability to response to the latter problem, it tend to focus on a single factor; there is no existing method that is able to reduce the computational cost while maintaining the high level detail of simulation. Almost all the existing models were agent-based (microscopic models). This approach describes the most natural way to simulate crowds as independent autonomous pedestrians interacting with each other. Such algorithms usually handle local collision avoidance and global navigation for each person. However, these kinds of models have the drawback that when animating a large crowd, they are computationally intensive. Microscopic models give more accurate result only for smaller crowds to achieve real time simulation. On the contrary, the macroscopic models are usually created to realize a real time simulation for very large crowds; they follow the features of the flow as long as the overall crowd behavior seems realistic. These models offer a coarse-grained simulation result with higher execution efficiency which is due to the lack of concerns of individual issues.

Secondly, modeling the movement and behavior of the virtual crowd remains a major challenge as highly dynamic complex systems, the crowd is a large group of pedestrians with non-uniform spatial distribution and heterogeneous behavior characteristics, and it exhibits often distinct characteristics, such as independent behaviors, self-organization, and pattern formation, due to interactions among the individuals and groups of individuals. Previous work has suggested that human crowd dynamic can be modeled on many different scales [108, 110], from coherent aggregate behaviors of the crowd on the largest scales to the individual behaviors, interactions among individuals on the small-scale detail. Such multi-scale systems are computationally expensive for traditional simulation techniques to capture over the full range of scales [110]. Another large class of problems which are not easily handled by traditional approaches is the simulation of very large aggregates of discrete entities, such as dense pedestrian crowds and granular materials.

To overcome these conflicting goals, we assume a scalable simulation is required to handle at least several hundreds or even thousands of pedestrians, running in real-time, particularly with respect to the complexity of the environment and the realism of behaviors required by the crowd, we investigate to find a good balance between visual credibility of complex crowd behaviors and computational requirements, where the behaviors of human crowd can be viewed on a two different level of detail: from the chaotic, fluctuating interactions between individual objects on the finest scales, to the coherent aggregate flow of the system on the largest scales.

Our solution consists to introduce a hybrid simulation architecture that combines the strengths of two classes of crowd modeling to achieve flexible, interactive, high-fidelity simulation on large environment. This architecture couples a microscopic model of individual navigation with a novel continuum approach for the collective motion of pedestrians; it can apply to simulate the behaviors and movement patterns of extremely large crowds at near real-time rates on commodity hardware.

Our approach is able to determine by itself the most suitable model of modeling for each region in the environment, regarding the simulation context, in real time and within a continuous environment. To do so, we first introduce the generic notions of dynamic change of representation, and we describe my methods for handling the transfer of pedestrian between continuum and discrete simulation areas and discuss how the constituent simulation components are adapted to handle this transition.

Then, we evaluate this approach experimentally along two criteria: the impact of our methodology on the computational resources, and an estimate of the dissimilarity between a full microscopic simulation and a simulation with our methodology. Finally we discuss the results obtained and propose enhancements for future works.

3. The proposed model

This research addresses the possibility to design and implement an integrated behavioral framework to build real time simulation of the dynamics of large scale crowd with a wide variety of individualistic human-like behaviors. The problem is that crowd simulations need a scalable architecture that simultaneously supports the realistic simulation of hundreds of thousands (or millions) of complex autonomous agents, while allowing such simulation to achieve with good frame rates.

We develop a crowd simulation model which preserves the granularity of simulation at the individual level, and at the same time is scalable and can simulate combined behavior of huge crowds. To achieve realistic simulation we should ideally be able to model the activities of every individual, even when there are thousands of such individuals.

Our proposed model is based on the two-layer modeling principles: (1) modeling the agent and (2) modeling the environment that agents interact with. The use of two conceptual layers allows us to isolate modeling of the environment and agent. The interaction between the layers is analogous to the interaction between humans and their surroundings in the real world. The agent makes decisions based on the perceptions from the environment and executes decisions to achieve its goal in the environment.

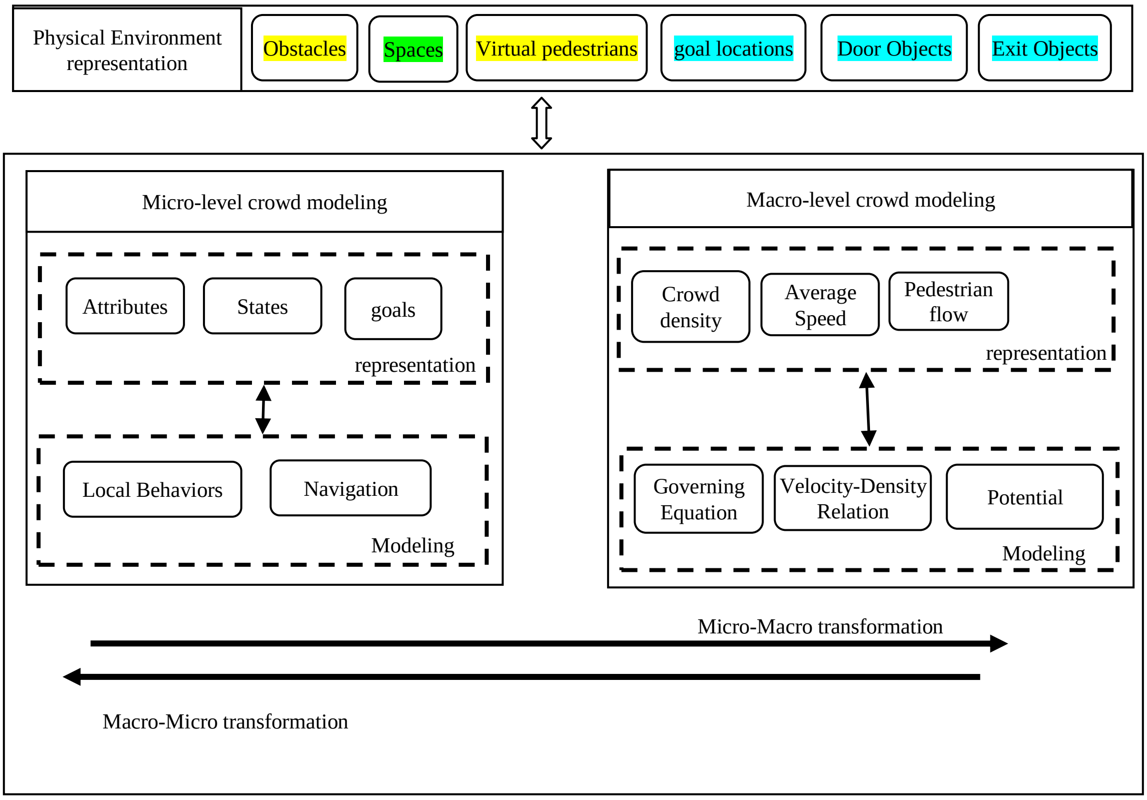


Figure 6. 1 Hybrid Model for crowd simulation

3.1. Physical Environment representation

This module is the basis of crowd simulation, because the virtual human chooses the path and action according to his/her location and surrounding information. For example, sensing obstacles and other people to make avoidance, keeping standing pose in escalator and walking on flat surface. To represent a physical environment in our proposed model, a set of geometric information of the physical environment is selected to construct a virtual environment. Selected geometric information includes obstacles, spaces, exits, and doors. The geometric information are extracted from the 3D structure of the simulated environment.

- ✓ Obstacles. Obstacles refer to walls, furniture, and any objects that are inaccessible. Each obstacle has definitive boundaries. Agents detect the obstacle through their sensors.

- ✓ Spaces. Spaces are the areas in which agents may maneuver freely. Examples are corridors, lobbies, and rooms. The shapes and dimensions of spaces are obtained based on the arrangement of obstacles.
- ✓ Exit objects: each exit object represents an outlet of the building. If an agent decides to escape through a specific exit, it navigates toward the location recorded in the exit object. When the agent reaches the exit, it is removed from the building.
- ✓ Door objects: a door object is similar to an exit object, it connects spaces and allows an agent to transit from one space to another. However, upon arrival to a door, an agent is not removed from the building.

3.2. Crowd model

Crowd model is the second element of our proposed model which generates path, behavior and locomotion for each virtual human according to the information of a given environment. The representation of crowd model is described by two main classes: macroscopic and microscopic models. Each approach is associated with its own distinct advantages and disadvantages.

3.2.1. Macro-scale crowd modeling

Macro-scale crowd modeling is concerned with group behavior and deals with a crowd as a whole. It interprets a crowd as a several number of pedestrian group where all individuals share the same space and have a common goal and the same walking ability in a simulation. People in crowds act similar to one another, often acting in a coordinated fashion, as if governed by a single mind. individual who becomes a part of the crowd is loosed their individuality and transformed into becoming identical to the others in the crowd.

In this sense, macro-scale model is mainly useful in estimating the flow of movement/evacuation process for huge and dense crowds. It animates the crowd flow by the help of a set of partial differential equations describing the time–space evolution of macroscopic traffic variables: flow $f = f(x, t)$, speed $V = V(x, t)$, and density $\varphi = \varphi\,(x, t)$[59].

The flow (f) denotes the number of pedestrians passing a cross-section of a pedestrian facility in a unit of time. The customary unit for flow is P/ms (pedestrians per meter width per second).

Crowd density (φ): is defined as the number of pedestrians present on an area at a given moment, it is measured by counting the number of pedestrians and divided by the area in which the pedestrians were counted. The customary unit for density is $\mathrm{P/m^2}$ (pedestrians per meter square).

The speed (V) stands for the so-called space mean speed which is the average speed of pedestrians present on an area at a given moment (m/s).

In order to get a realistic representation of crowd movement, the perspective of macroscopic modeling approach consists to describe the dynamic of pedestrian and its density by using a scalar two dimensional conservation law. The direction of the flow is determined by the route choice strategy, and a linear speed–density relation is assumed to determine the magnitude of the pedestrian speed. The continuous equations in the mathematical model are converted into discretizations in time and space.

Although, the approach modeling in this level unifies global path planning and collision avoidance since the continuum equations takes the goals, obstacles and other pedestrians into account when predicting the motion of a pedestrian. We discretize the environment into a regular 2D grid and constructs the continuous values of density and velocity, at various locations within each grid cell, that guides the virtual humans toward their goals without colliding with each other or with other dynamic and static obstacles.

3.2.2. Micro-scale crowd modeling

In micro-scale crowd modeling, the crowd is modeled as a collection of heterogeneous, autonomous, decision-making entities called virtual pedestrians which inhabit a spatially explicit, partially observable environment; macro-level dynamics are said to emerge through the asynchronous interactions among these entities.

Agent-based approach is more suitable for simulating situations involving heterogeneous pedestrians and dynamic environment. Each individual in these models is considered as an agent with varying attributes of gender, age, body size, mobility, walking speed and other capabilities. In the developed model, each person has its own:

- ✓ Characteristics (average and maximum speed, maximum energy level, obedience, knowledge of the surroundings)
- ✓ State (position, speed, energy)
- ✓ The objectives to be achieved (to leave the building, to escape the room).

In the implemented simulator the person is represented by an agent who makes decisions and performs large variety of individualistic behaviors with consideration of a set of characteristics, states, the objectives to be achieved and the state of the environment.

One key aspect of these behaviors is navigation. In the context of crowd simulation, navigation is generally considered to be the process of planning a route towards a destination and following this route. It is typically generated from activities of an agent at two levels: path planning and locomotion. Path planning can be considered as the higher-level behavior that generates a global path directing the agent to the goal. This typically considers static aspects of the environment, such as walls and doorways. Locomotion is considered as the lower-level behavior that actuates the agent's motion in order to avoid dynamic obstacles.

4. Environment Model

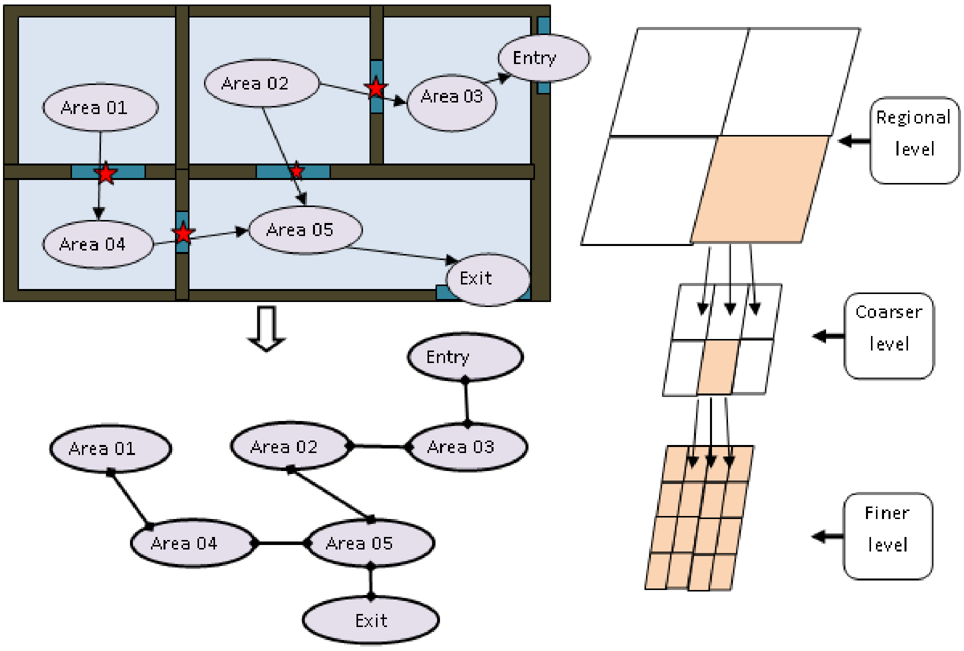
The environment in which the simulation takes place is the surrounding of the pedestrians, where they move along, interact and navigate to get from one location to another, typically, it includes walk-able areas, obstacles of different natures, and destination. Whereas, fixed obstacles can be defined as regions that no pedestrian can access, moving obstacles are other pedestrians occupying predefined space from the environment which is consequently not anymore available.

The first step in designing a crowd navigation system is to construct an efficient abstract representation of the virtual environment where the pedestrian can rapidly perform way-finding. We define a representation method which handles two types of structure data to clearly represent and to organize the topological relationship among the different geometrical areas of a large complex environment. This approach provides a well consistence resulting from the continuous interaction between two models of different level of detail.

4.1. Topological graph

Usually, the virtual environment is defined by a 3D model to constitute a geometric representation of the real world. Such representation of the spatial data makes it difficult to handle by virtual pedestrian in order to find its own paths through the environment. The most way to facilitate this representation is to obtain the topological relation of the environment and its geographical areas captured in a graph based structure (Fig.6.2(a)).

The topological graph uses nodes and edges to indicate the adjacency, connectivity, the inclusion and the intersection between the different parts of the environment, in which the node defines spatial areas and the possible path can be defined as edge. The internal spatial areas can be defined as a bounded volume in 3D space (such as a room, a corridor, a flight of stairs or even an entire floor) with bottom flat that contains several objects inside it (e.g., ground, walls, benches).



(a) Topological graph representation of the virtual environment

(b) Hierarchy model for environment representation

Figure 6. 2 Our model for representing the virtual environment

4.2.Layered model for environment representation

The second form of space representation is to use the layer structure (Fig.6.2 (b)). We identified three independent layers related to the model used for simulating the behavior of virtual crowd, each of which contains both static and dynamic data. Then we implemented the following layers for representing each spatial area in the environment:

- ✓ Regional layer. In this level, the whole walking space of one spatial area is divided into a number of unique continuous sub-areas. For generating these sub-areas, one main requirement must be valid which is: these subareas must be exhaustive; two different must not cross each other. This level is used to precise which model must be used for movement modeling, macroscopic model in the subarea with high density, and the microscopic in the other sub-regions.

- ✓ Coarser layer. The surface of sub-area, defined in the regional level, is assumed to be divided into cells; we do not limit ourselves to a maximum of one pedestrian per cell, in contrast, we consider each cell's size to be sufficiently large enough to contain at least 25 individuals of average size, where individuals placed on the same cell do not overlap.
- ✓ Finer layer. Every cell from the coarser layer is further divided into a uniform lattice of cells, each representing a portion of the simulated environment and comprising information about its current state, both in terms of physical occupation by an obstacle or by a pedestrian. The size of the subareas could be reduced to the average space occupied by a single pedestrian.

5. Crowd model

We propose a hybrid framework (Fig. 6.3.) for real time simulation of pedestrian dynamics and movement patterns of huge crowd in a complex virtual environment. This solution preserves the granularity of simulation at the individual level to capture individualistic pedestrian behaviors, and at the same time is scalable and can richly exhibit emergent behaviors of dense crowds.

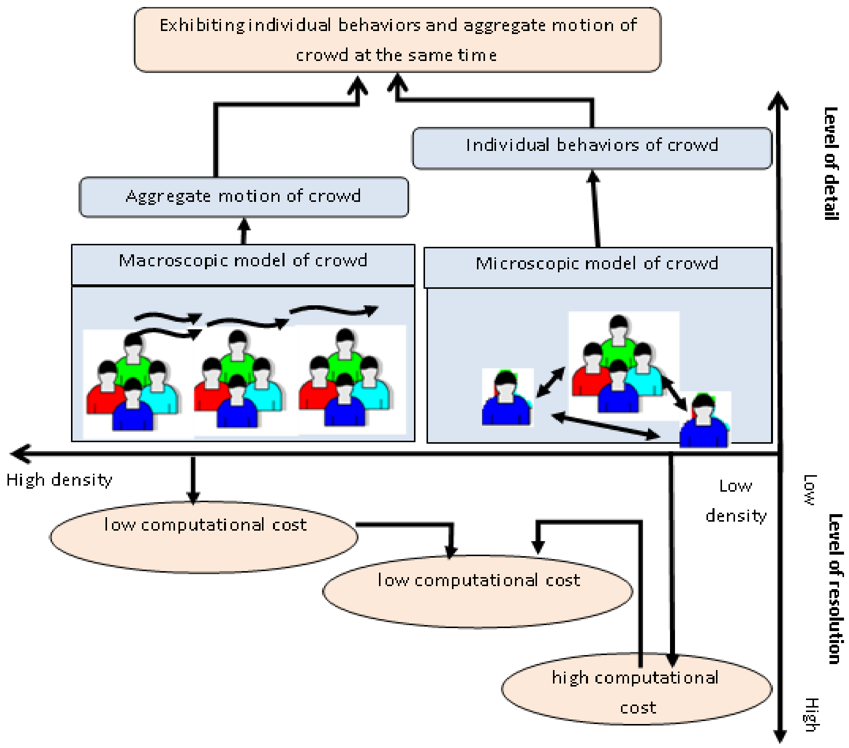


Figure 6. 3 Proposed crowd model

Our proposed architecture consists to integrate a more detailed approach with a coarser model, describing the individual pedestrian behaviors and crowd dynamics, within an unified crowd modeling framework, and execute them simultaneously in different regions of the virtual environment.

There are several reasons which have motivated our decision of a proper coupling of two philosophies of modeling focusing on different level of detail (discrete individuals and crowd as a whole) executing to produce most visually pleasant simulation.

First, pedestrian crowd is a multi-scale phenomenon, which can be described at both macroscopic level (continuous medium) and microscopic level (granular medium), in many scenarios, it is need to have pedestrians behave individually, continuously interacting with other pedestrian while trying to reach their own objectives, thus the behaviors of each pedestrian must be treated more precisely. In other situation, pedestrians' flows demonstrate some striking similarities between pedestrians' behaviors and particle flow dynamics. Hence the flexibility of combining two models of different level of detail is examined to capture and characterize the almost aspects of the crowd dynamic.

Macroscopic models allow a better overall understanding by regarding the crowd system as a whole rather than on the details, and are usually designed to achieve a coarse grained simulation executing in real-time for very large crowds as long as the overall crowd movement looks realistic.

Microscopic models focus on individual behaviors including pedestrian's psychological and social characteristics, interaction among pedestrians, and complex cognitive behaviors. Although microscopic models are very accurate only for modeling smaller crowds to achieve real-time simulation, they can simulate pedestrian in a crowd with more realistic individual behaviors.

Secondly, a multi-methods simulation can give a good equilibrium between computing resources and simulation properties, such as realism, coherence and complexity. The microscopic models can generate a fine-grain simulation in more detail than the macroscopic method. However, they have high computational and memory needs. The macroscopic models can save resources but tend to give less accurate results. Mixing both types of models can hopefully allow combining the strengths of both classes of crowd modeling to achieve flexible, interactive, high-fidelity simulation on large virtual environment.

However, this fundamental choice leads to several challenges which can be classified along two axes.

- ✓ The first key important of our hybrid technique is related to the execution of the models themselves. We must precise how the two different types of simulation will be used (the two models executes interchangeably or simultaneously), and the way they will coupled together.
- ✓ Finally, the second challenge focuses on the needs to manage the transfer of pedestrians between macroscopic and microscopic areas and we must discuss how the constituents of our hybrid framework are adapted to handle this transition.

With the aim to achieve these two fundamental challenges, in our hybrid, multi-method technique, we divide the simulation environment into multiple disjoint (and not necessarily connected) areas each area is ruled by either microscopic simulation or continuum simulation. These mutually exclusive regions are dynamic, we can adaptively change the simulation method used in a specific region as needed cording to its density, meet performance requirements, or to observe certain phenomena (individual behaviors or crowd movements).

In the zones of high density of crowd the individual behavior is less critical, we assume to govern the crowd behaviors by a continuum approach to exhibit the aggregate motion and to describe behaviors similar to granular flows. On the other regions of low density, a realistic behavioral model is used to microscopically model the pedestrians. Our architecture also ensures that no visible disturbance is generated when switching from one model to another. To achieve this, we must be able to convert discrete pedestrian from microscopic simulation regions into the aggregate format necessary for continuum simulation (or vice versa).

5.1.Pedestrian agent model

In this section, we adopt an agent-based modeling approach to design a behavioral framework for the simulation of human crowds whose main innovative element is the representation and the generation of natural and realistic navigational behaviors of highly heterogeneous pedestrians in different environments under various situations. These behaviors of the virtual entities should be consistent with observed behaviors in real life.

In our proposed model, at the microscopic level, the crowds are modeled as collections of interacting individuals that move in a bounded environment. Each pedestrian wants to reach his individual goal in space, avoiding obstacles, and remaining close to his friends or family.

Virtual characters (or agents) need to autonomously find and traverse paths through the environment. Agents should act in a realistic manner: their trajectories must be short and smooth, there should not be any collisions between agents, and the agents are typically expected to mimic human behavior. Emergent behaviors can also be observed in crowds, e.g., in places where the space is small and very crowded, people form lanes to maximize their speed. Also, when dangerous events occur, pedestrians tend to react in very chaotic ways to escape.

It is well known that the first step of the agent-based modeling of crowd dynamics involves the identification of the following elements:

1. Each individual has its own parameters. The parameters of an agent consist of two parts: roles and attributes. Roles define the types of behaviors an agent is capable of during the simulation. It is simulation scenario dependant (See details in "simulation and discussion" section). The agent's attributes are used to describe the agent's characters and abilities which could influence the calculations of behavior effects. Attributes include: position, body size, orientation, movement mode (walk or run), base movement speed, maximum movement speed, and base movement speed adjusters.
2. A set of agent relationships and methods of interaction—an underlying topology of connectedness defines how and with whom agents interact.
3. The agents' environment—agents interact with their environment in addition to other agents.
4. Knowledge. Knowledge represents the agent's familiarity with the surrounding environment which comes from a spatial analysis of the agent's awareness range, varying from the individual's vision to the entire scene. The agent makes his strategy, e.g., path selections, according to his knowledge.

From a computational modeling point of view, complex navigational behaviors have been typically modeled through two levels of activities of an agent: path planning and locomotion. Path planning can be considered to be the higher-level cognitive activities that generate a global path directing the agent from its current position to the goal. It typically considers the static aspects of the environment, such as walls and doorways in the relatively long term in both spatial and temporal domains. Locomotion is a lower-level cognitive activity to move the agent along the path while avoiding collisions. This bi-level methodology is effective in some applications, but lacking when it comes to the reflection of the naturalistic cognitive process of pedestrians and the generation of realistic navigational behaviors.

We distinguish three aspects of motion planning that need to be addressed if we want to obtain realistic results. It is commonly agreed that self-organization is the result of elementary actions that each subject performs to fulfill specific wills. Concerning pedestrians, the following basic guidelines can be identified:

- ✓ The will to reach specific targets, e.g., an exit or a meeting point, which drives pedestrians along preferential paths, determined mainly by the geometry and the spatial arrangement of the walking area.
- ✓ Path planning: how to get from point A to point B. Given a goal, we usually plan our path according to various criteria: avoid zones where the traffic is too dense, reduce the distance to cover, minimize travel time, etc.
- ✓ Obstacle avoidance: to safely reach a goal, one also needs to avoid static and dynamic obstacles in the environment. Static obstacles usually are objects that do not move, such as trash cans, streetlights, signboards, etc. Dynamics obstacles typically are all other moving entities, including cars, animals, and especially, other pedestrians.

We propose a generic multi-level hierarchy for solving agent navigation problems, and we present our algorithms and implementations of the each level. The structure of the framework, computational methods, and essential algorithmic procedures related to representation of physical environments, sensing, behavior modeling, and collision detection are described in chapter 4. The simulation process of the proposed agent-based model is depicted in Fig. 6.4., which is executed in each simulation step.

Agent-based approach offers several advantages: (i) capture the variability of different individual characteristics and providing heterogeneity to the motion, (ii) captures emergent phenomena; (iii) provides a natural environment for the study of certain systems; and (iv) is flexible, particularly in relation to the development of geospatial models.

However, agent-based methods are costly in that each agent must be handled separately, comparing its state with every other agent. Several simplifications on agent-based methods have been offered such as local methods, pre-computed static plans, global planning on coarse environments and leader-follower models. However, an alternative to agent-based approaches has emerged from the fluid dynamics studies by making an analogy between the crowds and natural phenomena such as the behavior of fluids and gases.

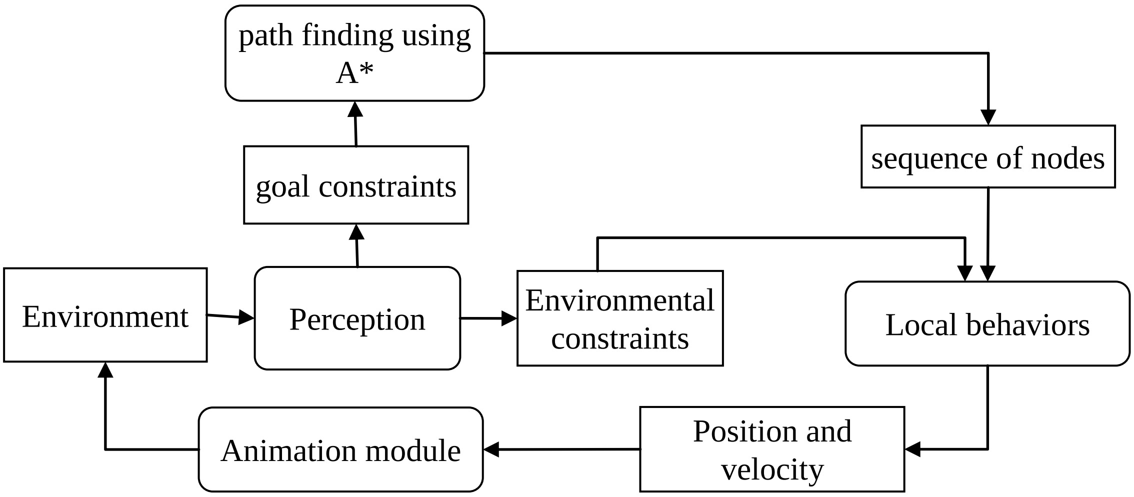


Figure 6. 4 Agent based model

5.2. Macroscopic scale modeling.

To overcome the inadequacies of the proposed agent-based model, we develop a fluid-like continuum model for macroscopically modeling the self-organized dynamics that are occurring in the pedestrian crowd, this model mainly consist to resolve the evolution of velocity and density over time. The intention is to show that this approach is well suited for the description and simulation of various aspects of pedestrian crowds, especially in the case of multiple intersecting streams.

This approach is more suitable for an aggregate representation of pedestrian movement over a large population, in this context, virtual pedestrians are not identified individually in the model, but an analogy to fluid flow is instead used.

The dynamic behavior of pedestrian is purely defined at the macroscopic level, for instance based on variations in time or space of the macro crowd variables and of a priori known equilibrium conditions: the value towards which the macroscopic variables would converge in the absence of variations in space and time.

Similar to vehicular traffic, we recall that the main characteristic quantities for the description of pedestrian streams at the macroscopic level are density, flow and speed:

Density. The concept of density describes a relationship between the number of individuals existing in a specific space and the size of this space. The density value of a selected measuring region ρ_A at frame i could be calculated using the following formulas:

$$p_i(x, y, t) = \begin{cases} 0, & (x, y) \notin A \\ 1, & (x, y) \in A \end{cases} \qquad (6.1)$$

$$N_A = \sum_{1}^{N} p_i(x, y, t) \qquad (6.2)$$

$$\rho_A = \frac{N_A}{A} \qquad (6.3)$$

$$A = b \cdot \triangle l \qquad (6.4)$$

where p_i represents whether a pedestrian was in region A (b: corridor width, $\triangle$ l: length of measuring region) at frame i; N signifies sum of trajectories and N_A denotes the number of pedestrians in region A at frame i; (x, y) is the position of an individual at frame i.

The associated density

$$\rho = \frac{A}{N} \qquad (6.5)$$

is measured by counting the number of pedestrians N within the selected area A at the time t.

The pedestrian area module, defined as the reciprocal of the density, has been introduced as another way of quantifying the pedestrian load of facilities. The density [59]

$$\tilde{\rho} = \frac{\sum_j A_j}{A}$$

which is the ratio of the sum of the projection area A_j of the bodies and the total area of the pedestrian stream A. Since the projection area A_j depends strongly on the type of person, the densities for different pedestrian streams consisting of the same number of persons and the same stream area can be quite different.

Another alternative density definition is based on averaging over a circular region of radius R,

$$\rho(\vec{r}, t) = \sum_j f(\vec{r}_j(t) - \vec{r}) \qquad (6.6)$$

where $\vec{r}_j(t)$ are the positions of the pedestrians j in the neighborhood of $\vec{r}$ and $f(\dots)$ is a Gaussian, distance-dependent weight function $\exp(-|\vec{r}_j(t) - \vec{r}|^2/R^2)$.

Velocity: velocity refers to the average velocity of pedestrians in an area at a specific time, it measures the distance per unit time, and its units are m/s.

The average velocity of N_A over the measuring region could be calculated using the following equation:

$$v_i(t) = \sqrt{\dot{x}_i(t)^2 + \dot{y}_i(t)^2} \qquad (6.7)$$

$$v_i(A) = \frac{\sum_1^N v_i(t) \cdot p_i(x, y, t)}{N_A} \qquad (6.8)$$

where $v_i(A)$ represents the space mean velocity of N_A over the measuring region at frame i.

Flow: The flow of a given measuring region could be calculated through the following formula:

$$J_A(x, y, t) = \rho_A(x, y, t) \cdot v_A(x, y, t) \qquad (6.9)$$

where, $J_A(x, y, t)$ represents the instantaneous flow over the measuring region.

The flow f of a pedestrian stream is defined as the number of pedestrians crossing a fixed location of a facility per unit of time. The most natural approach determines the times t_i at which pedestrians have passed a fixed measurement location. The flow is then calculated from the time gaps $\Delta t_i = t_{i+1} - t_i$ between two consecutive pedestrians i and $i + 1$:

$$f = \frac{1}{\langle \Delta t_i \rangle}, \quad \text{where } \langle \Delta t_i \rangle = \frac{1}{N}\sum_{i=1}^{N}(t_{i+1} - t_i) \qquad (6.10)$$

Another method to measure the flow is suggested by the analogy with fluid dynamics. The flow through a facility of width b is related to the average density ρ and the average speed v of the pedestrian stream,

$$f = \rho v b = f_s b \qquad (6.11)$$

where the specific flow

$$f_s = \rho v \qquad (6.12)$$

gives the flow per unit width. This relation is the hydrodynamic relation that we have already encountered in vehicular traffic.

The crowd's speed is subject to the density. The speed monotonically decreases from a ''preferred speed'' down to zero with the density varying from zero to a present maximum value.

The model always chooses the route via which requires the shortest time to reach the destination. We defined a cost function and a potential function for this purpose: The cost function, written as c(x, y, t), represents the minimal time cost for the pedestrians at a given location to move a unit distance, which is determined by the density of pedestrians at this location; The potential function, written as $\phi(x, y, t)$, defines the time to reach the final destination. The potential function can be calculated given that the neighboring points with the minimal value of the cost function are always chosen from the current location to the destination. The cost function and the potential function can be quantified using an Eikonal Equation:

$$|\nabla \phi(x, y, t)| = c(x, y, t).$$

After the potential function is resolved from the above equation, the minimal time from any point to the destination can be obtained. The pedestrians in the crowd will choose the route with the direction opposite that of the gradient of the potential function, $\phi(x, y, t)$. Eventually, the crowd movement is governed by a conservative equation:

$$\partial\rho(x, y, t)/\partial t + \nabla \cdot (v(x, y, t)\, \rho(x, y, t)) = 0.$$

6. Interaction between models

Our approach proposed here for the design a hybrid crowd simulation model concentrates on the integration of two models that have different level of resolution in order to capture at the same time the micro and macro dynamics of human crowds. This type of simulation has the ability to divide the environment into multiple disjoint areas and to simultaneously execute these two models in different regions, by using a macroscopic modeling approach to simulate pedestrian flow in region of high density and a detailed microscopic model to simulate individual behaviors of pedestrian in the other regions. Investigating this integration makes clear two hard problems to be encountered:

- ✓ First, assuring the consistency between the models is important for maintaining semantic continuity of results in terms of space (discrete/continuous), behaviors, and time, when concurrent interactions occur, if pedestrians pass from microscopic scale to macroscopic scale and vice-versa.
- ✓ Final issue consists to provide an efficient strategy for changing adaptively the simulation method in a specific region. It needs to identify the conditions in which a suitable modeling approach can be selected.

6.1.Transition of pedestrians

As mentioned above, inconsistencies can arise in our hybridization solution when persons can be transformed from one model to another of different scale. To achieve this, an interface translating boundary condition is needed to define for moving those pedestrians from a continuous to a discrete modeling approach. We adapt this case by defining a boundary area adjacent to the macroscopic region; this bound is divided to cells, only the pedestrians in this area transform to the microscopic scale, i.e. if there are when pedestrians enter this area forcibly changing their representation levels, their positions, orientation and velocity will updated by the microscopic model.

There exist two basic communication operations between the two models: aggregation and disaggregation (Fig. 6.5.). The disaggregation refers to the process of generating the initial parameters for the microscopic model based on the result from the macroscopic model. Correspondingly, aggregation is the operation where the collects statistics from microscopic model and the parameters are generated in the format as required by the macroscopic model.

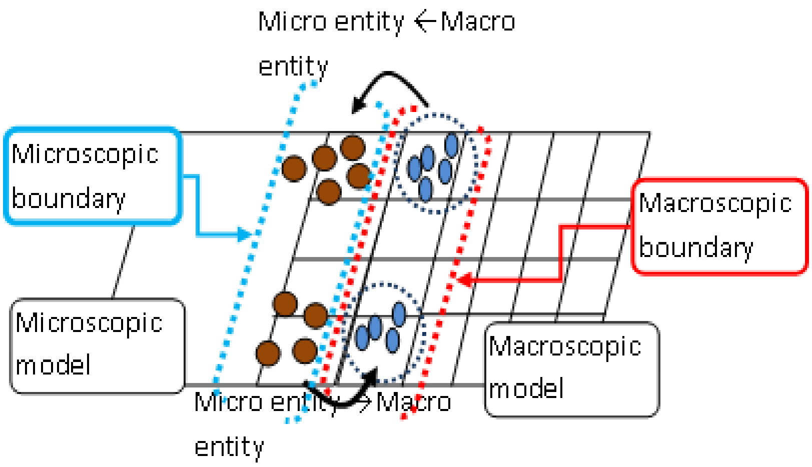


Figure 6. 5 Interaction between micro and macroscopic model

6.2.Trigger

Our hybrid approach of modeling consists to combine two models of different level of detail of simulation in a single framework; it attempts to provide a scalable and accurate method for the autonomous navigation process. The whole continuous simulation environment is divided into multiple mutually regions, defined at initialization. Each region is governed by one of two different motion modeling approaches, either macroscopic model or microscopic model.

According to the density of crowd, the model used in a specific region is determined at initialization and modifiable at runtime. Then it is very important to present an efficient technique to define how the simulation changes dynamically from one model to another. Density is another fundamental component of pedestrian flow models. As the density of pedestrians' increases, pedestrians will have less space to overtake other slow pedestrians and eventually the average walking speed is slowed down. Usually when the pedestrian density is higher than 5~6persons/m^2, the average walking speed is so low that the crowd can hardly move any more.

- ✓ **Switching Micro→Macro** we calculate the density in each area. This operation occurs when the density in an area ruled by microscopic simulation is larger than a predefined threshold, then the system should trigger the execution of macroscopic model in this region.
- ✓ **Switching Macro→Micro** we calculate the density in each area, It consists to switch the simulation in a specific zone from a macroscopic to microscopic model; this is occurred when the density of this region is smaller than a threshold. Then the microscopic should execute.

6. Conclusion

In this chapter, we detail a crowd behavior model that realistically handles crowd motion planning in real time, it is proposed to reflect the differences among the behaviors of the virtual agent in different density. Our approach provides a complete solution for all three aspects of crowd motion, i.e., path planning, following path, and individual level and crowd level behaviors.

To obtain high performance, our approach is scalable: we divide the scene into multiple regions of varying interest, defined at initialization. According to its density, each region is ruled by a different behavior modeling algorithm. Zones with low density exploit accurate methods, while computation time is saved with less expensive algorithms in other regions.

In the zone where the crowd density is low, each agent acts freely according to his intent so that he can do everything he wishes, we are concerned by applying an agent-based model to show a large variety of the individualistic behaviors.

When the density of the crowd is high, the surrounding agents will impose more mental stress on each other and people show a tendency towards mass behaviors. In that case, we use a macroscopic approach to simulate the crowd behavior.

Our hybrid model also ensures that no visible disturbance is generated when switching from an algorithm to another.

Chapter 7: Results and evaluations

1. Introduction

One of key objectives for this work is to facilitate the cooperative use of disparate simulation strategies agent-based and continuum crowd simulation to handle the simulation of at least several hundreds or even thousands of pedestrians, running in real-time, particularly with respect to the complexity of the environment and the realism of behaviors required by the crowd, we investigate to find a good balance between visual credibility of complex crowd behaviors and computational requirements

There are numerous reasons that this is desirable: continuum crowds approach is useful and efficient when large homogeneous groups of people are moving in order to reach specific goals and has performance advantages over agent-based simulations in many situations | its computational cost is proportional to size of the virtual crowd. At a time step, motion planning is computed for each group people consisting of the agents that have the same destination. This characteristic meets our requirements since we can define the agents that are all trying to reach same specific goals in the same way as a group. The amortized cost per agent is substantially reduced if groups include lots of agents. We need a mathematical model, which is derived from the hypothesis about the virtual crowd, to simulate crowd dynamics.

Furthermore, in the heterogeneous crowded situation, the agent-based approach is the most natural one since it is the way that real crowds work: each human makes his own motion decisions according to only the information he has, such as visibility, information about the destination, and proximity. However, this approach has the disadvantage that when animating a large group of people, it requires large computational time. Agent-based models have the flexibility to add any intended variation to the animated crowd, since each agent can be modeled differently but it needs expertise to model every agent consistently.

This chapter summarizes the results of the proposed approach. In Section 1, the microscopic algorithm will be tested in different scenarios. The aim is to subjectively evaluate the experimental results to determine the performance of collision avoidance and motion update algorithms. Later, the macroscopic method is implemented for allowing large-scaled crowds to run in real-time.

2. Performance of Hybrid Model of Real Time Crowd Simulation

In this section we present and describe the experiments for the evaluation of our hybrid model for interactive visual simulation of large scale crowd of virtual pedestrian. Our solution model is specifically designed to support robust real time simulation of scenarios with thousands or even hundreds of thousands of pedestrians. It involves the combination of two significantly different types of modeling methodologies for taking the advantage of their complimentary features, in which a macroscopic model is applied where needed and a microscopic model where plausible.

In order to evaluate the effectiveness and the robustness of our multi-modeling approach presented in this paper, we have conducted to realize a number of simulations with different initial distributions and conditions (mainly changing the density of pedestrian crowd in the environment) in a situation in which experiments focused at analyzing the impact of the density of crowd on the pedestrian behavior that could be handled was being investigated.

The objective of the experiments which we use is to show the proposed model performs well to produce results that closely simulate real human behaviors in these situations, and to study whether the proposed model can describe the qualitative dynamic properties of the pedestrian's movement under situations with three different level of density (low, medium and high density) in terms of number of pedestrians that could be handled with reasonable performance.

We tested our system on virtual complex environment, in order to produce realistic crowd behaviors in this type of space; the simulation environment itself should have the features (properties) of real life environment. We also believe the representation of the environment has an important influence on pedestrian navigation. In this section we demonstrate the application of the hybrid approach using the arbitrarily complex geometry. The structure has a free floor space area comprising of 7 irregular shaped rooms with two external exits.

The pedestrians are initially distributed randomly over the area of the environment. The particular distribution of the density pedestrian was selected to ensure that during the simulation all two possible modeling approaches: Macroscopic model; and microscopic model; would be used. We performed a series of experiments in order to test the behaviors under study focusing on showing the results of the interaction of the two sub-models.

2.1. Experimental Results: Path-planning and collision avoidance of microscopic crowd Simulation

Fig.5.1 shows the simulation results of the pedestrian dynamic produced by the microscopic model which is selected to apply according to the pedestrian density calculated as the numbers of pedestrians existing in the restricted areas under consideration.

2.1.1. Scenario 01: Shortest path of individual pedestrians

The results when using path-planning algorithm for computing the shortest route are discussed in this sub-section. Fig. 7.1(a) shows the initial configuration of the simulation. In this scenario, 120 agents are dispersed onto the limited zone. Motion planning using microscopic approach and without continuum model are specified in this context.

A normal collision avoidance method is implemented initially. In every simulation step, the new position of each pedestrian is calculated based on his velocity. Collision detection is executed and the pedestrian's position is updated to the newly elevated position, as long as the pedestrian does not collide with others in the newly estimated position. If any colliding happen, the pedestrian will not be moved and the current direction will be updated by adding an offset angle. This method is simple to implement, but has a major drawback: penetration and deadlock can happen in case of high density crowd, due to the limitation that in each time frame, the direction of agents can be updated once only. There are chances that two objects will collide when updating with the new direction.

To address these issues, we introduced an RVO structure. Firstly, RVO can help avoid collision. Secondly, a new motion planning method is estimated by using three types of path-finding algorithms to resolve deadlocked conditions. The results are explained and analyzed below. Note that flow fields are used to visualize the performance of the algorithms.

Results show that the pedestrians in two groups can avoid collision and reach the goal perfectly by using our motion planning algorithm. The different stages of the simulation are shown in Fig. 7.1 showing two crowds meeting in the middle of the zone, at the middle of the simulation. Fig. 7.1 shows the final stage of simulation where the crowd has reached the destination.

The flow field for this scenario is given in Fig. 7.1 and Fig. 7.2, which maps the motion of the two groups. The directions keep changing constantly to find a free path and subsequent target tracking can be clearly seen at several locations in the flow field. Our motion planning algorithm can guide pedestrians to find free paths perfectly, and there are no congestions between the two groups when they meet in the middle of the scene. Another major advantage is that the deadlock situation is always avoided. In this experiment, pedestrian distribution is scattered. Note that to increase the density of the crowds in the next experiment.

This model is considered to be qualitatively more accurate than the macroscopic model. This experiment shows that when the number of virtual pedestrian is small (Fig.7.1), the microscopic modeling approach has been employed to simulate each pedestrian as an individually entity with its own its own personality, and its behavior which is determined by both the global and local movement.

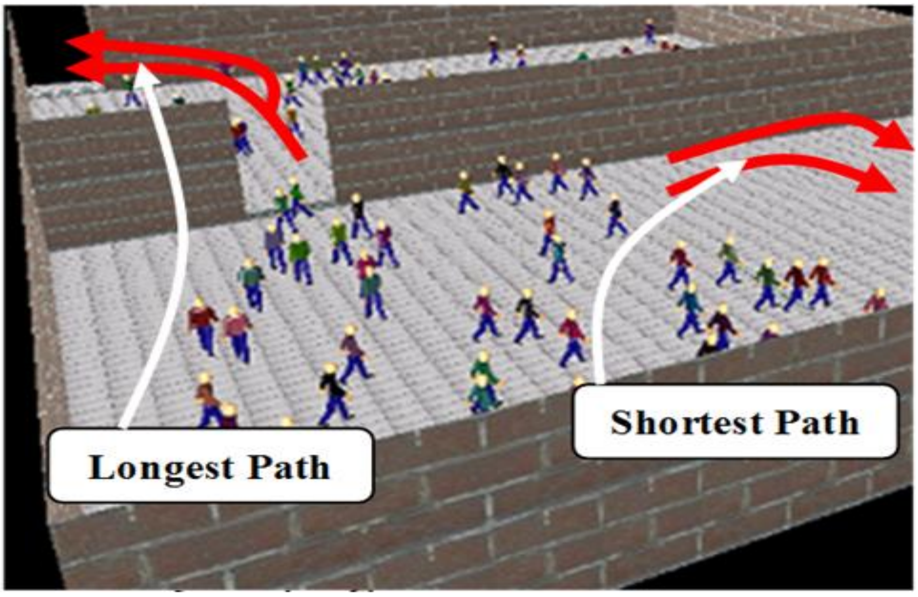


Figure 7. 1 Agent-based approach to find the shortest path individually for each pedestrian

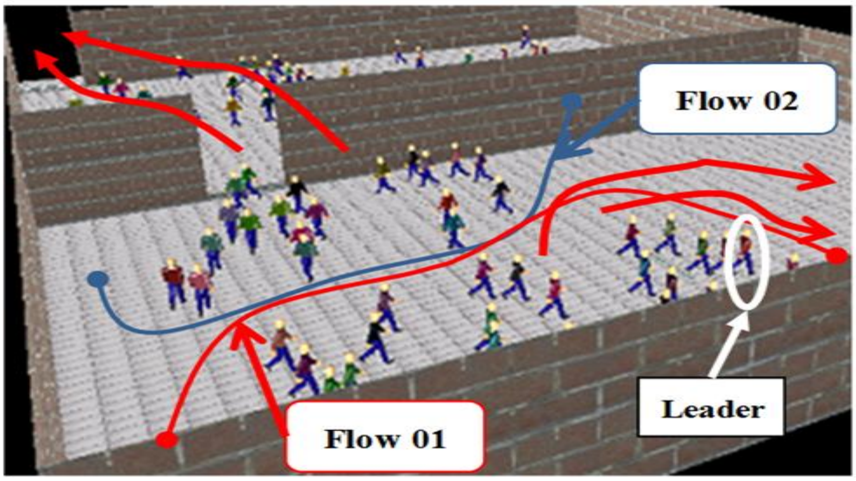


Figure 7. 2 Following route behavior to achieve pedestrians'goals

2.1.2. Scenario 02: Medium-density Crowds

To evaluate the motion planning algorithm further under extensive conditions, we increased the crowd size from 100 to 300 agents. The total travelling times for different crowd size are measured. Congestion starts occurring when the crowd size is 500. This could be due to the narrow width of the zone. The congestion increases many-fold, owing to the increasing crowd size.

In this scenario, we demonstrated that a leader has a major influence on people especially in evacuation situation, in order to formulate the leader-follow behaviors. Fig.7.3 shows this case, when, we can observed the red flow follow a leader which has a global view of the simulated environment, then he find the shortest path into the exit, but the blue flow has no leader, then he choose the shortest door which leads it to follow the longest path (Fig.7.4).

So far, the collision detection is only considered between agents. We increased the complexity of this environment by adding three obstacles in the middle of the scene, a situation where we could have collisions between agents and obstacles. This set up also allows for testing and evaluating the obstacle avoidance algorithm.

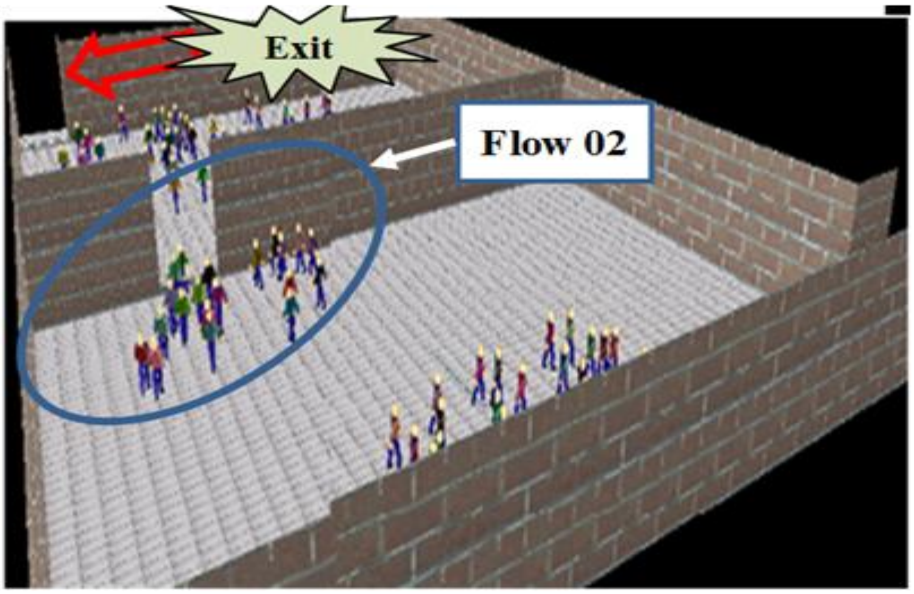


Figure 7. 3 The leader find the shortest path, and the flow 1 follow it

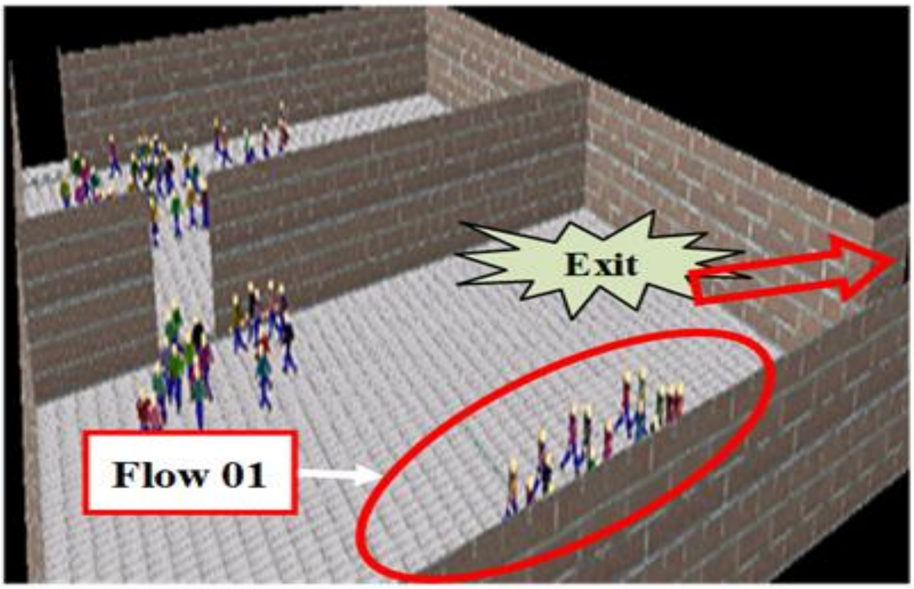


Figure 7. 4 Flow 1 follow its shortest path

2.2. Experimental Results: Small group and pedestrian flow of macroscopic crowd Simulation

During the second experiment, we noticed that pedestrian's density increases in the same subarea; the macroscopic is adopted to handle the pedestrian's behaviors within a crowd of high density. This model facilitates the construction of small groups of individuals that shows a slight cohesion and natural fragmentation into subgroups that might be simple and therefore much more compact.

2.2.1. Scenario 01: Group phenomenon

Group phenomenon is an interesting area of research for pedestrian simulation, because it is very common in the every-day life, people standing closer to its familiars and forming small groups. In panic situation, people relatively tend to gather together closer. In these situations, people are mostly linked by the (temporary) sharing of a common goal, and the overall group tends to maintain only week compactness, with a following behavior between members.

In Fig. 7.5, the macroscopic used to cluster the pedestrians into a structured group by assuming a common goal, passing a direction and speed that applied to all of the members. As a member of a group, each pedestrian coordinates with others in the same group and show an aggregate motion as they move together.

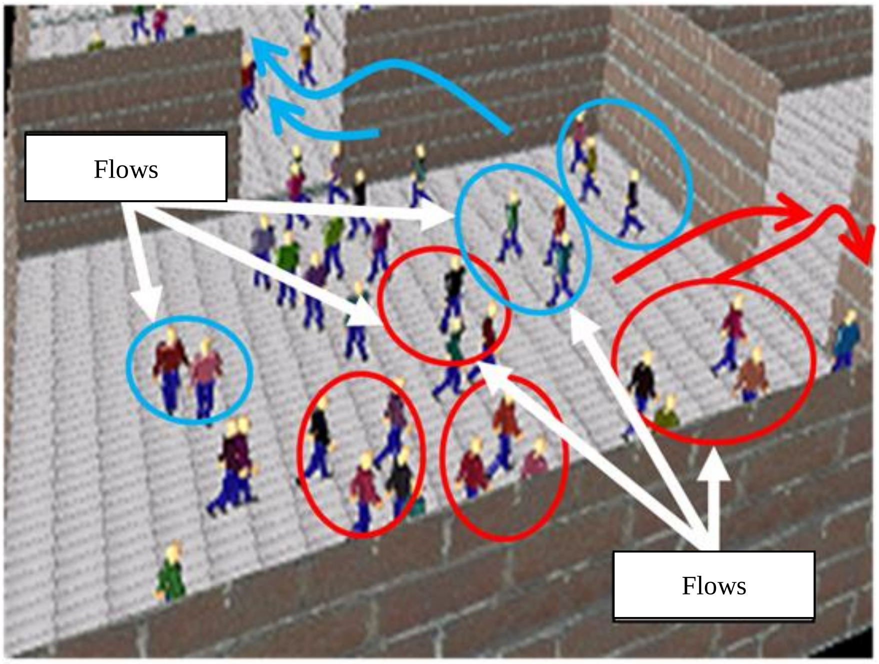
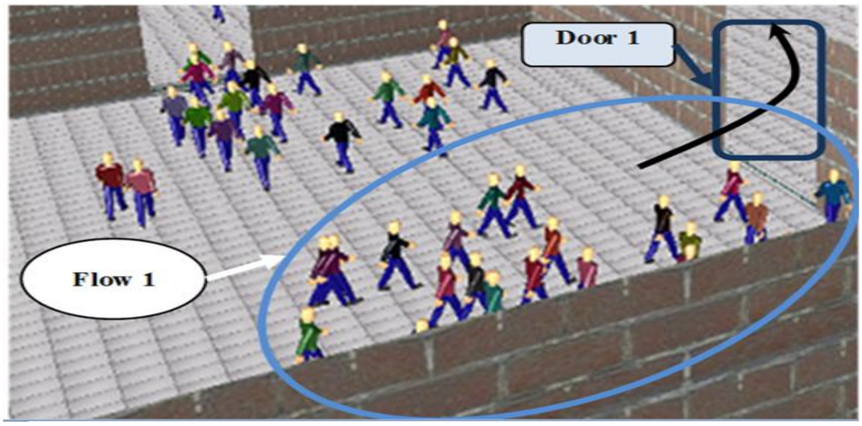


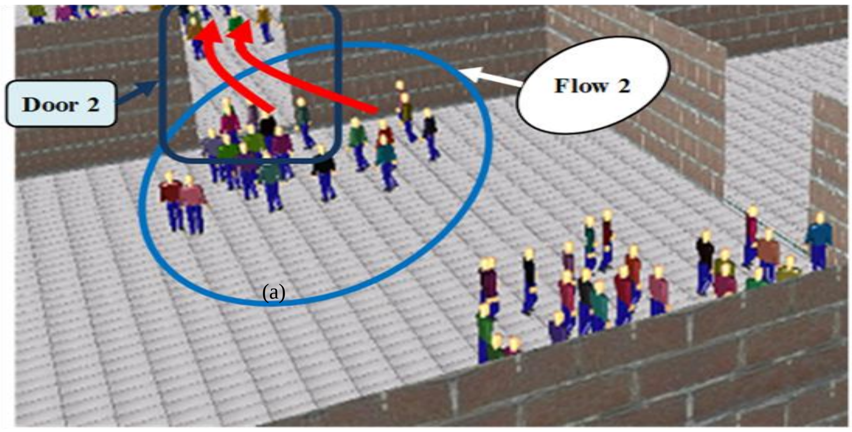
Figure 7. 5 Creation of small pedestrian flow in normal situation.

The last simulation results in Fig (7.6) show that in crowded situations, (pedestrian's density increases until it reaches a maximum value when situation becomes congested), one of the typical phenomena occurring in pedestrian flow is self-organization of lane phenomena. In the real life, pedestrians in a crowded area tend to self-organize into lanes in order to reach their destination faster and easier.

As a result of the lane formation, pedestrians walking towards the same destination, they tend to automatically arrange in virtual lanes which reduced the potential conflicts with opposing pedestrians.



(a)



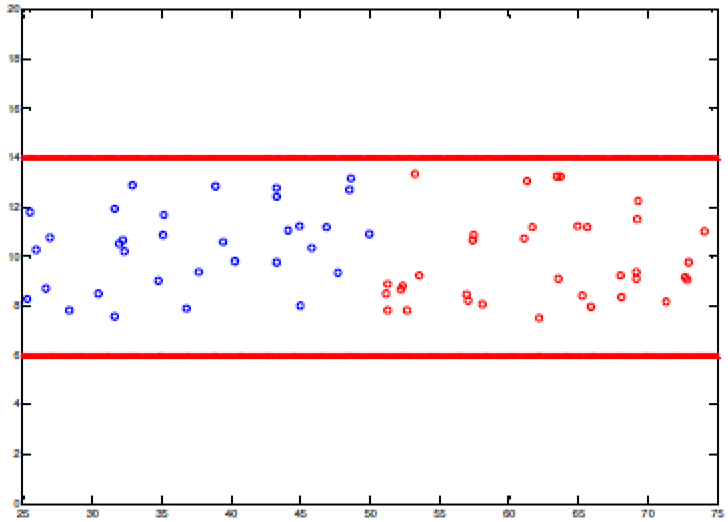
(b)

Figure 7. 6 The small groups follow themselves for forming a flow

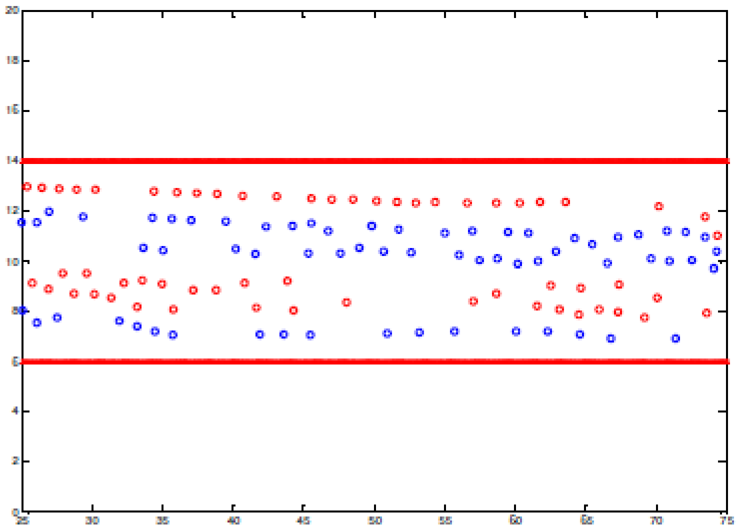
3. Pedestrian Counterflows

In this section our model will be implemented and used to simulate pedestrian counter-flows both with and without a bottleneck in the walkway. The purpose of modeling these situations is to assess the validity of the simulation in a qualitative sense. In chapter 1 certain emergent phenomena were discussed; in particular lane formation in a counter-flow and oscillatory flow at bottleneck. For these particular geometries a more detailed analysis of the pedestrian movements will not be considered, rather this section aims to confirm that the model simulates well experimentally observed phenomena ([1], [2]).

In a counter-flow expected emergent behavior is lane formation as discussed in chapter 1. The simulation was run for 250 pedestrians on a 200 meter walkway which is 6 meters wide. Half the pedestrians were randomly placed at each end of the walkway (Fig. 7.7 (a)). The wave front of each the pedestrian bodies (in this case the group at either end) meet at the middle of the walkway.



(a) The initial pedestrian positions created for a counterflow

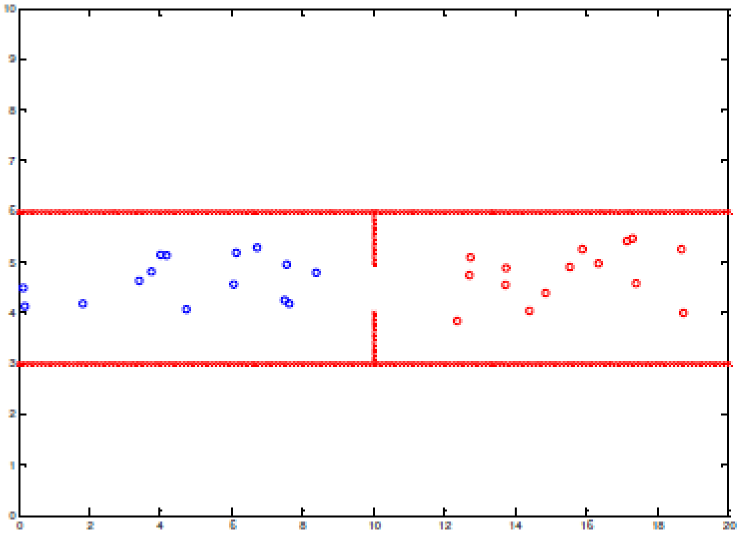


(b) The final pedestrian positions created for a counterflow

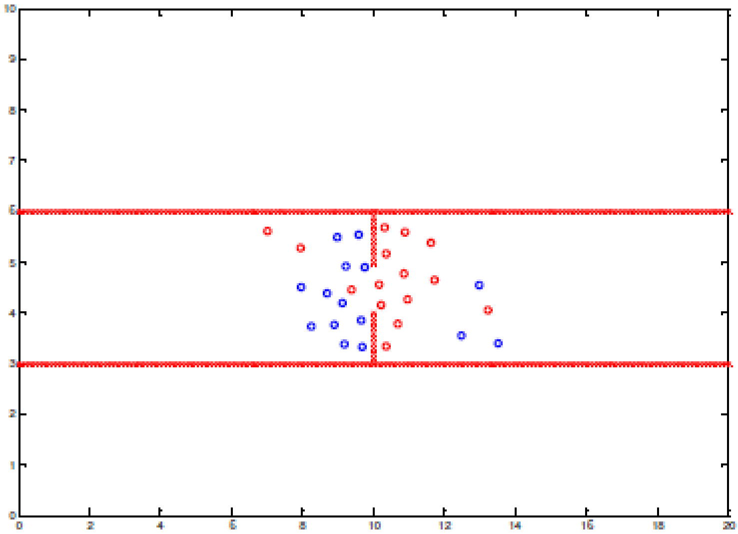
Figure 7. 7 Counterflows behavior

The results of the simulation are better than expected, reproducing the self organization phenomena perfectly. However these results underline the idealized nature of the implemented model (Fig.7.7(b)). In a real counter-flow the pedestrians would not be homogeneous, that is the desired speed of the walkers would not be uniform and the pedestrians radii would not be the same. These inhomogeneities would lead to behavior that isn't observed in this simulation, a particular example of this would be overtaking maneuvers performed by faster moving pedestrians. In walkways with large pedestrian densities these maneuvers can lead to a breakdown in the lane formation; this suggests that these idealizations may not always be valid assumptions.

The next geometry to consider is a counter-flow with a bottleneck. In this case the bottleneck refers to a doorway although in practice it could be a longer bottleneck (c.f. the test room geometry). The bottleneck, a 1 meter wide doorway, is positioned in the middle of the walkway which is 3 meters wide. 30 pedestrians were placed randomly, with half at each end of the corridor.

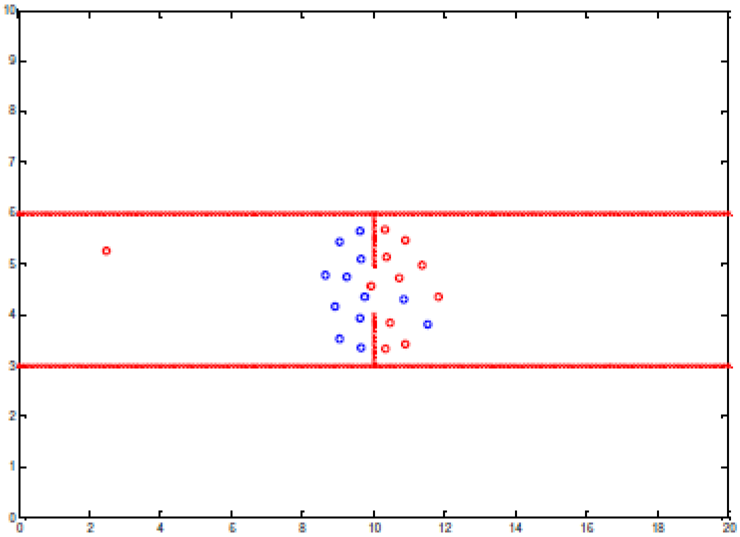


(a) Initial Pedestrian Positions

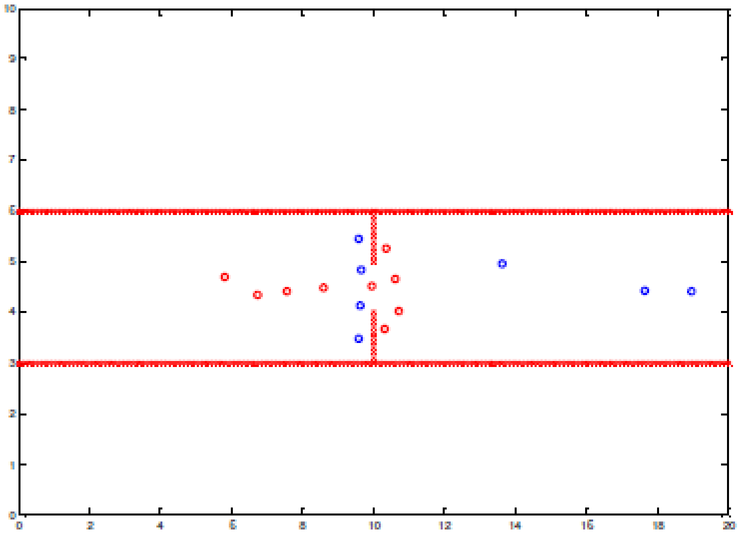


(b) Pedestrians meet at Bottleneck right moving (red) pedestrians flowing through

Figure 7. 8 Initial phase to simulate counter-flow behavior with a bottleneck.



(a) Switch in flow-now the left moving (blue) pedestrians are flowing through



(b) The flow has switched several times, now the right moving pedestrians are passing bottleneck

Figure 7. 9 Counter-flow behavior with a bottleneck.

The figure illustrates the oscillatory flow through a bottleneck is reproduced by the simulation. This oscillatory behavior is much clearer in the associated movie. Again the results of the simulation are consistent with the experimental data of Helbing [1].

4. Street flows

A characteristic of local virtual environment is narrow passages between zones. We expect a crowd model representing behavior in such a context to exhibit behavior associated with these constraints, namely that flows form allowing for faster traversal of agents through a passage. We believe that the presence of flows can be quantitatively identified based on the following parameters:

- ✓ Passage width: If street flows are forming then narrow passages encourage the formation of streams of individuals in opposite directions which convey both crowds efficiently though the gap.
- ✓ Number of agents: If street flows are forming then the emergence property of flows requires that flows start forming only from a certain crowd density.
- ✓ Randomness: If street flows are forming and an agent stops, the speed of the agents behind it on the same flow decreases rapidly and thus the overall speed rate of the crowd drops quickly with an increasing number of stops.

Below, we conduct experiment with these parameters and provide evidences that support the existence of flow formation.

4.1. Passage width

We examine the rate of two groups of agents passing through a narrow street in opposite directions.

In the absence of flows, we expect plentiful collisions and the rate at which the groups pass through the alley should be proportional to the width of the passage i.e. the wider the passage, the faster the crowd passes through. Our expectation is that this will not be the case if flows form, specifically because flows provide for efficient traversal even through narrow passages.

We conducted a simulation with two crowds, each containing 20 agents. Each crowd starts on opposite sides of the passage (where agents are spaced across the full width of the passage).

The time taken for both crowds to cross the passage in their entirety is measured for passages of different widths.

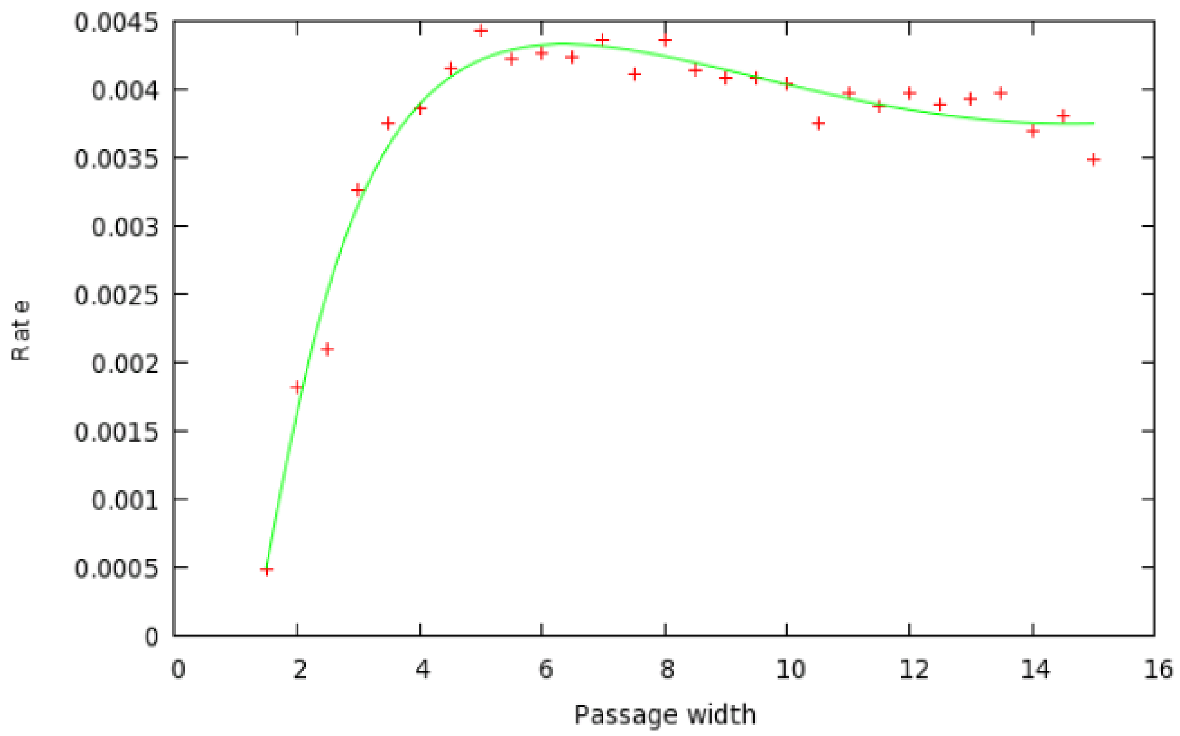


Figure 7. 10. The measured time taken to cross passage with different width

The rate t (the reciprocal of the time taken to traverse the passage) is plotted in Fig.7.10. We observe that the rate is zero or low for very narrow passages, which is expected as the passage is limited to only one person at a time. The rate increases rapidly as the passage opens up until it reaches a maximum at which point it decreases slowly with increasing passage width. We attribute this to the formation of flows: narrow passages encourage the formation of streams of individuals in opposite directions which convey both crowds efficiently though the gap. As the passage gets wider, individuals break away from the flow when gaps open up and eventually collide with flows in the opposite direction which reduces the overall rate slightly. This hypothesis is supported by visual observation of simulated agents.

4.2. Number of agents

We conduct another simulation of two crowds, fixing the passage width to 3.0 units and increasing the number of agents for each simulation. The rate is plotted in Fig.7.11. We observe that the rate drops with the increase of the number of agents (as expected) but the rate does not drop as rapidly after the number of agents exceeded 3. We attribute this to the emergence of street flows which can only occur once a sufficient number of agents is present.

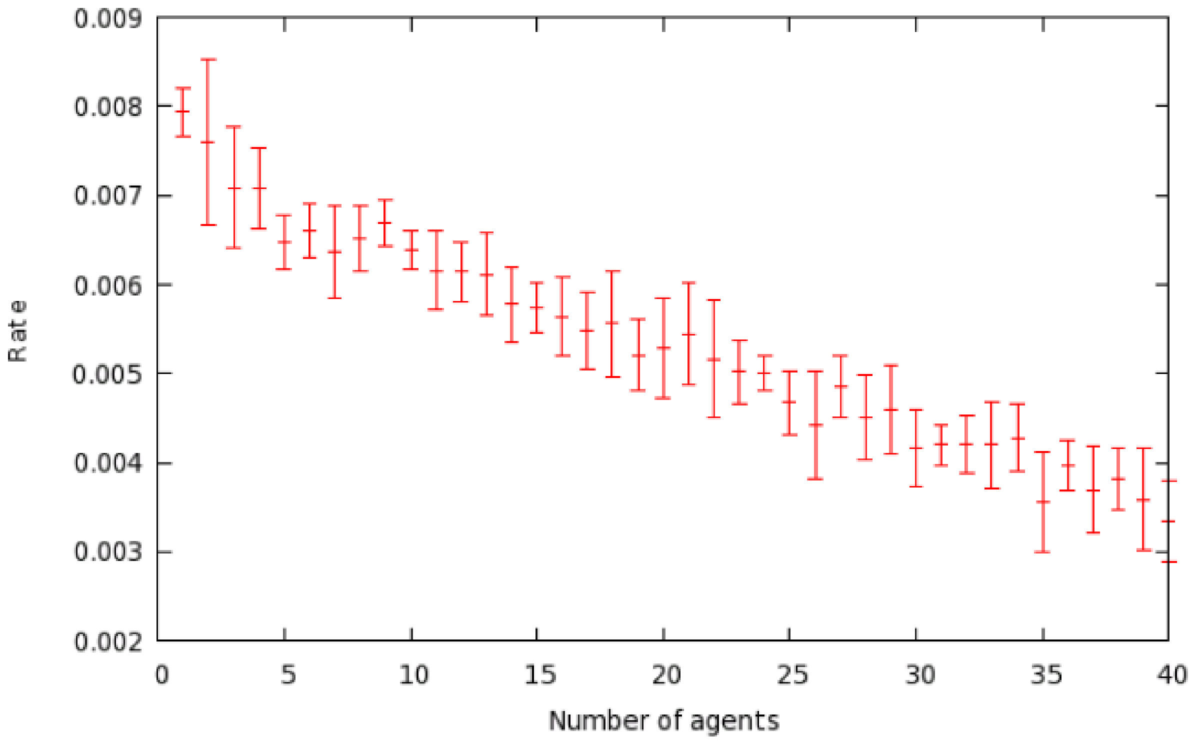


Figure 7. 11 The number of agents passing through a passage with fixed width

5. Conclusion

Multi-approach modeling is proposed in this work as an adaptive simulation strategy for exhibiting the pedestrian crowd movements and its emergent behaviors in high density situation. Our method makes it possible to exploit advantages from both macroscopic and microscopic models. The two types of models work simultaneously in a single simulation system, and are executed over different mutually exclusive partitions.

Our model also ensures that no visible disturbance is generated the crowd to move from one partition to another, and a suitable strategy is considered that is able to switch dynamically from one to another.

It would be worthwhile to investigate the addition of social behaviors to our method to enhance the realism of the results, and we anticipate that our approach can be explored emergent resulting from various types of behavioral rules. Further work, the coupling of mesoscopic models with our model will develop to apply in the region with middle density.

Conclusion

Realistic real-time motion planning for crowds has become a fundamental research field in the Computer Graphics community. The simulation of urban scenes, epic battles, or other environments that show thousands of people in real time require fast and realistic crowd motion. Domains of application are vast: video games, psychological studies, and Architecture to name a few.

We present the motion planning architecture of crowd simulation, offering a hybrid and scalable solution for real-time motion planning of thousands of characters in complex environments. Multiple motion planning approaches for crowds have been introduced. As of today, several fast path planning solutions exist. Dynamic avoidance and high-level group behaviors however, remain expensive tasks. Agent-based methods offer realistic pedestrian motion planning, especially when coupled with global navigation. This approach gives the possibility to add individual and cognitive behaviors to each agent, but becomes too expensive for large crowds. Potential field approaches handle long and short-term avoidance. Long term avoidance predicts possible collisions and inhibits them. Short term avoidance intervenes when long-term avoidance cannot prevent a collision. These methods offer less believable results than agent-based approaches, because they do not provide the possibility to individualize each pedestrian behavior. However, they have much lower computational costs.

Multi-approach modeling is proposed in this work as an adaptive simulation strategy for exhibiting the pedestrian crowd movements and its emergent behaviors in high density situation. Our method makes it possible to exploit advantages from both macroscopic and microscopic models. The two types of models work simultaneously in a single simulation system, and are executed over different mutually exclusive partitions.

It is important to notice that our resulting hybrid technique can automatically and dynamically select the suitable strategy; the dynamic switching between both models is ruled by the runtime simulation metric which is the crowd density in the partitions of the virtual environment. Our model also ensures that no visible disturbance is generated when adaptively change the simulation method in a region. The partitioning of the environment allows us to define transition zones where the two types of movement modeling approach must be interacted and crowd under one regime must be moved to the other.

We will continue to work on the proposed behavior model, which aims to be useful in different kinds of crowd simulation applications, our future work provides a development of a wide variety of social behaviors. These behaviors are managed for more accurate simulation results under various complex conditions by incorporating the more complex group structures and the interactions between the different types of pedestrians. Further work, the coupling of mesoscopic models with our model will develop to apply in the region with middle density.

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