An Information Processing Based Model for Emergency Egress Simulation

Vaisagh Viswanathan T

under the guidance of

Asst. Prof. Michael H. Lees

School of Computer Engineering

A thesis submitted to the Nanyang Technological University in partial fulfilment of the requirement for the degree of Doctor of Philosophy

March 2014

Abstract

Crowd egress is an area of research that has increasingly become more popular. Research over the past few decades have increased the current understanding of human and crowd behavior by leaps and bounds. During the same period, advances in technology and experience in modeling and simulation have lead to increasingly capable modeling and simulation systems.

This report presents the preliminary work done towards the author's thesis and describes some of the details of the proposed computational model of egress. A study of existing literature on crowd, egress and general human behavior reveals that, while there are a large number of theories of human behavior, there are a few characteristics of human behavior that have become well established. The fact that humans do not behave irrationally during a fire evacuation; rather, they behave rationally within the bounds of the information they have is a rather surprising one. Other salient features of egress behavior include the fact that there is a significant pre-evacuation period where the evacuee completes the task he/ she is doing, searches for more information to clarify the danger of the situation and finds his/ her primary group before they actually start the process of moving towards their preferred exit. The proposed model proposes to model these *salient features* of human egress behavior.

The purpose of this thesis, is to make use of most current knowledge of human behavior in creating a detailed Agent Based Model and Simulation of Crowd Egress from a building on fire. The model is based on the idea that humans are serial information processors who use the information about the world around them as much as possible to evacuate. This information can be in the form of obstacles that he/ she perceives; it can be events that he observes; it can refer to messages that are communicated between agents and it also includes information stored in the person's cognitive map to plan a route for escape. However, the limitations in information processing capability of the human brain and the experience and background of the evacuee makes it difficult for him/ her to know the best route, remember the nearest exit and perceive every single clue that might help him/ her. These are complications that are seldom considered in existing computational models of egress.

Acknowledgements

Thank you

Vaisagh Viswanathan T
Dec 2011
Nanyang Technological University, Singapore

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Managing crowd egress from buildings is one of the key challenges faced during all kinds of disasters ranging from fires to terrorist attacks to natural disasters like hurricanes and tsunamis that are becoming increasingly common today. Egress modeling and simulation provides an inexpensive, effective and efficient way to analyze and identify the issues that can affect efficient egress in such situations. Several models of crowds and egress have been developed over the years. However, there are still several areas of crowd behavior that have either not been considered in computational models or haven't been analyzed in sufficient enough detail to inspire confidence in their ability to forecast human behavior during an evacuation. This thesis attempts to advance the capabilities of computational models of egress by demonstrating novel models for aspects of egress that are generally not modelled and also by introducing some tools for analyzing and comparing certain aspects of existing models.

Recently, experts in various fields [1] are emphasizing the importance of recognizing the complexity of systems. They emphasize the need to model these complexities to have a realistic chance at understanding and predicting what happens in the real world. In recent times, one of the most popular methodologies for tackling this complexity has been through the use of Agent Based Modeling (ABM). An Agent Based Model is made up of multiple heterogeneous intelligent entities known as agents interacting in an environment. The bottom up approach of modeling each agent's behavior often allows the modeler to implement existing theories of individual behavior directly without having to abstract away too many details into an abstract mathematical formula. This approach is generally very useful because it is easier to study and formulate theories at an individual level; apply this theory to model a real world system populated by many such individuals; and finally simulate its working and correctness. Higher level patterns that emerge from this microlevel modeling can be analyzed and studied to learn more things about the system and make predictions. Thus agent based models are ideal for models where there is enough information about the behavior of individual interacting entities.

Crowd simulation is just such an area that has been the subject of a significant amount of multidisciplinary work over the last few decades [2? ?]. Its applications range from simulating crowds for movies [3, 4] and games [? ?] to analyzing pedestrian behavior [5? , 6] and preparing for fire evacuations and similar emergencies [7? ?]. One of the most famous recent applications was in animating large crowds in the award winning movie, Lord of the Rings, which used the commercial software called MASSIVE [3]. Another frequent user of crowd simulation systems is civil defense authorities who make use of these simulations to study, evaluate and formulate strategies for controlling crowds and for tackling emergencies that can emerge. The Sydney Olympics made use of crowd simulation software (LEGION) [2] to test the facilities for their ability to accommodate crowds and emergency evacuations. Still [2], while making the aforementioned LEGION model of crowds, conducted extensive surveys and analyses of videos to accurately model the movement of the crowds.

Even with all the complexity, detail and meticulousness of these models, many psychologists and sociologists are unconvinced about the efficacy and accuracy of the results produced by these simulations [8–10]. This is because even the most popular of these models make certain assumptions about human behavior that stand against evidence obtained over the past few decades through extensive studies in the social sciences and humanities [9, 10]. Several details of human behavior are wrongly abstracted away, when in fact they actually play a key role in determining the egress dynamics.

Modeling humans with complete knowledge of the spatial layout of the environment is one such abstraction that is often applied to agent based models of crowds. The limited capacity of the human brain in processing information [11] at any given time can have a significant effect on the way humans perceive the environment and form their cognitive map and thus their egress route. It can also affect the time taken by a participant to start evacuating because he/she might not know about the fire even if the symptoms are right in front of him/her. This is why it is sometimes mistakenly assumed that people evacuating from a building tend to behave irrationally; while the reality is that they are actually just reacting rationally to the limited information that they have [9, 12–16]. Ignoring this perceived *irrationality* reduces the reliability of these models.

There have been tremendous advancements in our knowledge of human behavior over the last few decades. However, the majority of the state of the art computational models make assumptions about human behavior without grounding them in the theories and findings from social sciences. Being a very inter-disciplinary field this kind of collaboration is absolutely essential.

1.1 Problem Statement

Several studies over the past few decades have changed our understanding of human behavior during fire evacuations. Some [9, 12–16] have shown how humans always behave rationally with the limited information that they have and that humans hardly ever panic and behave irrationally. Others have highlighted the effect of stress and time constraints on human behavior [17]. Torres's thesis [9] compared and analyzed the effectiveness of various theories in explaining a real life fire incident.

However, as highlighted by Aguirre [8], existing computational models of egress do not take into consideration a lot of these findings. For example, it is still common to model panic/ irrational behavior in evacuating crowds. Pre-evacuation behavior and the search for information are two general characteristics of the fire evacuation process that are very rarely considered in egress simulation models. The few computational models of egress that do consider pre-evacuation [18**?**] behavior are rather simple. In other cases, like the models of human motion and exploration used in existing models, there are several different approaches that have been used but a consistent methodology for their evaluation and validation is lacking.

To improve the capability of computational models of egress it is necessary to first identify the key buildings blocks of a behavior model. Following this, the shortcomings in each of these blocks can be identified and addressed.

This thesis aims at enhancing the capabilities of existing computation models of egress by proposing novel methods to evaluate and improve core aspects of existing models, and to model certain important aspects that haven't been given their due importance in existing models.

1.2 Key Contributions and Scope of this Thesis

Some of the key contributions of this thesis are:

- A multidisciplinary survey and analysis of current literature on fire evacuation and crowd behavior.

- A novel information based perception system that can model the complexities and limitations of the human perception system: This model was presented at the CyberWorlds 2011 conference.

- A new model for event identification which can be used for simulating pre-evacuation behavior and the process of information seeking. This phase of evacuation has been proven to exist by several studies but has been generally ignored in most computational models of egress. A novel computational model for modeling pre evacuation behavior was implemented and presented at the Pedestrian and Evacuation Dynamics 2012 conference in Zurich.

- A human computation based investigation of the nature of human spatial memory and human exploration of multi-storey buildings. This analysis produced some interesting results that has been submitted to ..... .

- A detailed quantitative comparison between popular models for movement. The methods used in this comparison provides a very useful tool for comparing existing and future models of crowd movement. The results of comparing three of today's most popular models: Lattice Gas, Social Force and RVO2 are also presented.

1.3 Organization of the Report

This report is organized as follows. Chapter 2 provides a comprehensive review of relevant theories and existing models and also provides a critical analysis of some of the most relevant ones. The following chapter uses the literature reviewed in Chapter 2 to identify the key building blocks of human behavior during evacuation. The following chapters identify and solve a key shortcoming in existing computational models of each of these building blocks. Chapter 4 presents an Information Based Perception Model and demonstrates and validates its capabilities and working through several experiments. Chapter 5 then presents a new model for event identification which can be used for simulating pre-evacution behavior and also demonstrates through simulations the importance of modelling pre-evacuation behavior. Chapter 6 begins with a novel game-based experimental approach to understanding the impact that memory and non-randomness have in the human exploration process. The analysis from this game is used to study exploration of indoor environments. Finally, Chapter 7 addresses one of the key issues in movement modelling in crowds. It presents a detailed methodology for comparison of existing motion planning systems and further provides an analysis of some of the most important motion planning models used today. Chapter 8 concludes the thesis.

Chapter 2

Literature Review

Crowds are typically seen as a large collection of individuals sharing a common location and undergoing some common experience [19]. Depending on the experience being shared, individuals in a crowd can think, behave and react in different ways. In this thesis, the focus is on crowds involved in emergency egress. Egress refers to the process of leaving a place, and emergency egress situations are situations in which a crowd tries to escape from danger due to fires, bomb blasts or other similar situations.

Crowd modeling and Egress simulation are not *new* areas of research in any sense of the word. A lot of researchers have worked on modeling and studying crowds and evacuations over the past few decades. These include psychologists, sociologists, computer engineers, civil engineers, etc. In fact, fire safety science is itself an active area of research with dedicated journals. In this chapter, the current state of research in the understanding and modeling of crowds and, more specifically, emergency egress simulation is introduced. Section 2.1 talks about the essentially inter-disciplinary nature of crowd simulation and the importance of understanding and utilizing the different viewpoints and approaches. Section 2.2 introduces the reader to some of the psychological and sociological theories of crowds and people's reaction to fires. Finally, Section 2.3 explains how some of these models and ideas have been translated into computer models and are being used today.

2.1 Multidisciplinary Nature

A complex system can be defined as a system with many interacting entities whose properties are well defined. Inequalities in spatial and temporal interactions at the microscopic level can lead to emergent macroscopic phenomena [20]. An emergency egress simulation is just such a complex system with a lot of interacting elements. This system is made of a large number of human beings, the building, fire, smoke, fire alarms and other entities which might be specific to the location or type of emergency. Besides physicists studying the physics behind the development and spread of fire and smoke, there are other scientists and engineers who work on computationally modeling the spread of fire or smoke and the different complexities involved. There are also fire safety experts who work on improving the effectiveness of fire alarms and PA systems and, in general, on improving the efficiency of egress. A lot of researchers also work on the element at the core of this complex system: crowds or more generally, human beings.

Many psychologists have been studying crowds and how individuals behave in crowds for over a century now and many theories have been developed. A lot of these theories contradict each other and there is generally little consensus on which is the best. Torres [9] provides an excellent comparison of the different existing theories of crowd behavior. He does so by comparing their effectiveness in explaining the fire that occurred at the Station night club in West Warwick, United States on Feb 20, 2003. Section 2.2, which presents and explains some of the existing crowd behavior theories, uses the findings from this thesis extensively.

How people interact with each other and act in a crowd is just one aspect of the person's behavior during a fire. For instance, people don't start evacuating the building as soon as they hear an alarm or as soon as they hear there is a fire. Each *cue* that he/she observes has a certain impact on the person depending on his/her identity, social role and the circumstances. There are a lot of studies [9, 16–18, 21] that examine the effect of different cues on egress behavior and the other aspects of what we shall refer to as *pre-evacuation behavior*. Kuligowski [21] presented a list of various cues and how each of them affects a person. She emphasizes how cues need to be perceived and interpreted and how the decision for an action is taken based on these cues.

How decisions are made is itself an active area of research. Besides the theories on crowd behavior, some studies [17, 18], also propose different ways in which humans make decisions during emergencies. There are also several other dimensions to understanding the behavior of individuals engaged in egress. Various studies [12, 22, 23] discuss the effects of culture on egress and others [24, 25] propose crowd simulation models with two different emotional models.

Computational models of egress, try to model and simulate a crowd engaging in emergency egress so that these situations can be effectively tackled. There are several different computational models of egress and each of them has their own advantages. The major difference in opinion among computational modelers is on the amount of abstraction to be used. Some models like network based models and flow models, do not explicitly consider humans but rather view crowds as a homogeneous entity. These approaches are simpler for the modeler and computationally less resource intensive. Still, some crucial details like flow rate through doorways and the rate of survival can be approximately measured and analyzed. Agent Based Models, on the other hand, use significantly lesser abstraction in modelling crowds and are thus capable of simulating the heterogenity in crowds. These approaches take a bottom up approach; by specifying each individuals behavior it can more accurately approximate real life behavior. There are also more detailed agent based models of egress simulation that model human memory and emotions. These different modeling techniques and models and their strengths and weaknesses will be discussed in more detail in Section 2.3.

However, some studies [8–10] criticize computational models made by engineers and computer scientists for not taking into account the considerable advancements in the understanding of human behavior made by psychologists and sociologists. In recent time, some models [26] have made a start in this direction by recognizing the need for behavioral models. However, as stated by Sime [10]

> To date the significance of human cognition, decision making and social behavior seems to be recognized, but has not been fully incorporated into the prototype working models ...

For example, the idea of panic or *non-adaptive behavior* is at the center of the several behavioral models [26, 27], but studies have shown that this concept is neither clearly explained [9] nor well accepted [10, 15, 23, 28–30]. Also, it is difficult to find computational models that model factors like *pre-evacuation behavior* and *incomplete knowledge* of evacuees.

As our knowledge of human behavior, emotion, social interactions and decision making expands, a more complex picture of human behavior has been emerging. Using this knowledge in egress modelling has been limited. With current advancements in technology, there are fewer reasons to make unnecessary abstractions. Computational models for simulating emergency situations should try to model as much of the complexity as possible to be useful and accurate. With this purpose, the next section gives an overview of the current state of knowledge about human behavior in crowds and emergency situations.

2.2 Current Understanding of Human Behavior in Egress

As discussed earlier, a fire evacuation is a complex situation to model and simulate. The main reason for this complexity is that the system has a complicated entity at its center: a thinking, feeling and socializing human being. To accurately simulate the evacuation of a building in an emergency situation, it is necessary to understand the behavior and decision making of the people taking part in it. As briefly mentioned in Section 2.1, there are a lot of conflicting views and theories on how humans behave in emergencies and why they behave as they do. However, there are also certain parts of human nature that are generally accepted to be true like the tendency to search for familiar surroundings [15, 23, 30, 31] and the constant search for information [16, 17, 32, 33]. In this section, the reader is introduced to some of the major accepted ideas on the nature of human behavior during egress and some of the major theories on the same.

2.2.1 Pre-evacuation Behavior

Ideally, when a fire starts a fire alarm goes off; all occupants hear this alarm and use the nearest safe exit to leave the building. However, this is hardly the norm. In most cases, occupants are used to hearing false alarms and often do not start to evacuate until they are completely sure that it is needed. On January 19, 2000, a fire in Boland Hall in Seton Hall University in United States killed three students because they had ignored the fire alarms assuming it was a false alarm [34]. This uncertainty about the authenticity of a first sign of danger isn't an isolated incident [10, 29, 30, 32, 33, 35–37]. So, when studying the behavior of evacuees, it is necessary to study and understand their actions right from the point the fire started [33] rather than the time at which they start evacuating.

During an emergency situation there are some changes in the environment that indicate that something is wrong or different from normal. These changes are called *cues* [16]. Cues can come in a variety of different forms. Fire and smoke are the typical and most effective cues for an evacuation. Fire alarms and people running about or instructing to escape are also cues. There are three kinds of cues [16]:

- Ambiguous Cues: Hearing noises or shouting, or seeing someone run.
- Verbal Cues: Instructions from a companion, announcement from the stage.
- Unambiguous Cues: Seeing smoke or fire, or seeing someone run with a fire extinguisher.

According to some researchers [30, 38], an ambiguous cue by itself does not cause a person to initiate investigation. Rather, the cue has to persist for a period of time before investigation begins and results in the finding of an unambiguous cue. Interestingly, according to [33] even unambiguous cues don't result in people immediately exiting the building, rather it initiates a complicated process consisting of information searching and affiliation which will be discussed in more detail over the next few paragraphs. test test

The effect of cues and the evacuee's reaction to it depends on many factors. The identity of an individual's primary group and its proximity and availability determines the reaction of a person to a cue [16]. The classic study presented in [**?**], participants where placed in a room with smoke. The experiment showed that when alone, 75 percent of the subjects reported the smoke. In the presence of two non-reacting others only 10 percent of the subjects reported the smoke during the experimental period. The effect of groups and grouping behavior will be discussed in more detail in Section 2.2.2. Various studies [15, 23, 29, 32, 33, 39] emphasizes the importance of the location and the person's role in the significance of cues. As an example, a fire alarm at home is more likely to cause a person to act than a fire alarm at their office, which will most likely be considered a false alarm. People's societal role determines their training and responsibility and thus their alertness to cues and the preparedness for reacting to it.

Their groups, location and environment aren't the only factors that influence people's behavior during evacuation. There are also a lot of *intrinsic factors* that influence how people react to fires. What these factors are and how influential they are have always been a matter of much debate. Over the years there have been several surveys [21, 23, 33] that discuss these intrinsic factors. Andrée and Eriksson's report [22] even had a cross cultural study that compared the evacuation behavior of Swedish students against the behavior of Australian students. Except for grouping behavior they found hardly any significant differences in the behavior during evacuations. Kobes et al., in their survey [12], compared some studies of evacuation behavior from the USA, Great Britain and Australia and commented on them being "identical in their essence". Some factors like age and gender were found to not significantly affect pre-evacuation behavior. A person's social role is one of the commonly accepted factors that influence evacuation behavior [12, 15, 23]. Factors like the person's experience with fires, training, disabilities, familiarity with the environment, etc. are accepted to have a great influence on pre-evacuation behavior.

Close to a hundred different studies on human behavior in fires were used by Kuligowski [21] to make a compilation of the factors that influence egress and more specifically pre-evacuation behavior. In this article, she suggests that the period that we term as *pre-evacuation* itself consists of two phases. Phase 1 is called *perception*. This is an important phase to understand; Just because a cue exists, does not imply that everyone perceives it. The Table 2.1 lists some factors that can affect this perception of a person and whether these factors increase or decrease the chance of the person perceiving the abnormality in the situation.

Kuligowski calls the next phase *interpretation*. During this phase, the person searches for more information to verify whether a fire has actually started and if it actually poses a threat that needs to be handled. Many studies [17, 38] have confirmed the importance of this phase, though sometimes they are known by different names. In [17] this phase is called *unconflicted inertia* to indicate how the person either continues what he's doing or tries to finish of his activity without actually beginning to evacuate. In [33], this phase is called *investigation* to indicate the search for information (Sect. 2.2.3 and Chapter 4) that enables the interpretation of the system. Regardless of what it is called, this phase consists of two parts (1) defining the situation as a fire and (2) defining the risk that the situation poses.

Kuligowski categorized the factors that influence these phases into two types: occupant based factors (which are equivalent to the intrinsic factors mentioned earlier) and cue based factors. These factors and their effects are shown in Table 2.1. Increases/Decreases signifies a cues effect on that particular phase. Also, cue based factors, do not simply consist of events, but also their nature and features.

It is a general misconception that people panic and stop acting rationally as soon as they see a situation like a fire. Several studies [9, 12–16] have disproved this claim. An important conclusion that can be made from the discussion so far, is that irrational panic is hardly ever the standard first reaction to seeing fire. Rather, people react rationally and try to gain more information so that they can act more appropriately according to the situation.

To summarize, in this section how the process of evacuation starts has been discussed. The process called *pre-evacuation* consists of two phases: perception and interpretation. Cues present in the environment indicate to the evacuees that there is something happening in the environment. These cues can be of different types and their effect varies based on certain factors of the environment and certain characteristics intrinsic to the evacuee. During the second phase people search for verification that the situation does indeed require some action and various cues and other factors help him towards this realization.

2.2.2 Crowd behavior

This section discusses different theories of crowd behavior that, in general, deal with the phase that commences after *pre-evacuation*. According to Tong and Canter [33] emergency egress is a *complex social process*. What this complex social process is, has generally been a matter of much debate with a great deal of conflicting theories on the same. In his PhD thesis [9], Torres categorizes the theories on crowd behavior into 6 general categories:

- **Social Breakdown Model**: According to this theory, a fire evacuation is characterized by competitive behavior (pushing and shoving). As competition develops traffic jams occur at the doors or passageways. This competitive behavior is because the individuals think only about getting themselves out without concern for the other trying to escape, low optimism and a large group size which makes people think that they need to push and shove to stay alive. This model suggests that the reason for deaths and problems during egress is because of *non-adaptive behavior*. Non-adaptive crowd behavior is the type of crowd behavior that does not adapt to an emergency situation and often leads to destructive consequences.

- **Hysterical Belief Model** : This model is also characterized by flight behavior and non-adaptive behavior. However its cause is slightly different. In this model, it is necessary for a collective belief in a generalized threat to develop

Table 2.1: Factors affecting Evacuation Behavior. The list of factors and their influences as presented in Kuligowski's survey [21]

Factors	Perception	2a: Definition of the Situation as a Fire	2b: Definition of the Risk to Self/Others
Occupant-based pre-event factors			
Has experience with fires	Increases	Increases	Increases
Has knowledge of fire/ training	Increases	Increases	Increases
Habituation with environment	Decreases	—[1]	—
Has knowledge of routes	—	—	Decreases
Has frequent experience with false alarms	—	Decreases	—
Has a feeling of security in the building	—	Decreases	—
Has perceptual disability	Decreases	—	—
Is older adult	Decreases	—	Increases
Is woman	Increases	—	Increases
Speaks the same language as others	Increases	—	—
Has frequent interaction with family	Increases	—	—
Occupant-based event factors			
Has a higher stress/ anxiety level	Decreases	—	—
Perceives a time pressure	Decreases	Decreases	Increases
Presence of others (especially loved ones)	Decreases	—	Increases
Proximity to fire / Visual Access	Increases	—	—
Sleeping	Decreases	—	—
A higher number of behavioral processes(>1)	—	Increases	—
Defines situation as a fire	–	N/A	—
Cue-based factors			
A higher number of cues	Mixed[2]	Increases	Increases
Consistent cues	—	Increases	Increases
Unambiguous cues	—	Increases	—
Social cues (others' actions) that are consistent with an understanding of a fire situation	—	Increases	Increases
Official source	Increases	Increases	—
Familiar source	—	Increases	—
A higher dose of toxic gases	—	Decreases	—
Extreme/ dense cues	Decreases	—	Increases
Visual/ audible cues	Increases	—	—
Risk Information	—	Increases	—

[1] Areas where no research is found is marked by —
[2] Research conflicted on the direction of influence of this factor

before people start panicking. This belief in a generalized threat, develops when people perceive ambiguous cues and then feel anxious due to certain factors, like a feeling of reduction in exit choices; this, in turn, leads to a feeling of unambiguity in believing in a generalized threat which they can counter by fleeing. Also certain *components of social action* need to have been completed that permit panic to occur. These components are characterized as being actions that are as per norms (i.e. not non-adaptive) and which are done for the benefit of the entire crowd or collective. Emergent norm theory can be considered to be a kind of hysterical belief model. According to this, there is an extended period of *milling* during which people engage with others and exchange experiences. During this period a consensus develops and leaders also develop. Everyone in the group follows the actions of the leader in a process referred to as *keynoting*.

- **Non-Social Model** : This theory's main proponent is Quarantelli [40]. According to this theory people largely act in a pro-social manner, yet there occurs a point where a collective threat becomes severe and conditions emerge where social bonds break down and actions designed for self preservation emerge. The key point of difference from the previous models is the importance given to social bonds and the association of flight or competitive behavior or panic with breaking of these social bonds (this is a necessary but not a sufficient condition). Also competitive behavior is associated with individuals and not the group as a whole as specified in the hysterical belief model. As above, a perception of dwindling number of exits is also a precondition.

- **Normative Model** : This model is characterized by people helping one another during the emergency egress and an overall lack of competitive behavior. This theory is also characterized by a tendency to fight fire.

- **Affiliative Model** : This model conceptualizes emergency egress as people engaged in stimulation seeking behavior by moving towards others they feel close to or running towards locations that are familiar. People are assumed to have cognitive maps and a cue triggers a tendency to try to restore congruity to their cognitive map. People seek familiarity to such an extent that they might even move towards a threat. Even competitive behavior is affiliative in nature, i.e., people try to exit with their primary groups rather than alone (as in the non-social model). This search for familiarity might manifest itself as a search for group members or in other cases as taking a familiar route or in others just moving towards locations that are familiar.

- **Self Categorization Theory** : In this model, the people's groups aren't fixed. They tend to develop a sense of 'we-ness' with others present in the evacuation. Drury et al. [41] showed that collective bonds may be strengthened and even created through the experience of an emergency. This is characterized by people helping strangers escape. This idea of dynamic groups are also presented in some articles [14, 19, 39, 42]. When part of a group, people tend to follow the group consensus. Leaders develop for groups and these leaders can impose their will on the group. Groups that are formed are highly dependent on context and other groups and in turn the individuals present. Groups aren't static, they have dynamic characteristics. When faced with an adversity (like a fire), behavior in a group reaches a common level with time. The elaborated social identity model (ESIM) for crowds was an extension to this theory proposed by Reicher [14] which proposed an even more dynamic model of social identity and group behavior where the social role or identity of an individual can be influenced by his actions and vice versa.

Tong and Canter [33] stated that there are three distinct strategies that people adopt in a fire, the first of which is to (try to) extinguish the fire, the second is to seek shelter and wait to be rescued and the third is evacuation. Most of the theories state that people engage in flight behavior, i.e. they attempt to escape rather than fight the fire. Only the normative model predicts a fire fighting behavior and this kind of behavior was shown by only 4 of the people surveyed. It is interesting to note that in over three quarters of the domestic fire incidences that occurred in the United Kingdom and Australia, the fire was extinguished either naturally or by the residents and the fire fighters weren't called [12]. However, as further highlighted in the same paper by Kobes et al. [12] there is very little literature on fire fighting behavior shown by occupants outside of this. This might be because of a difference in attitudes towards private and public property. Nevertheless, there is not enough evidence to show that fire-fighting is normally done by occupants. This, however, does not suggest an absence of altruistic behavior. Other models like the affiliative model and SCT model do suggest that people do show altruistic behavior in helping others who are part of their group or who they characterize as being part of their group.

All the models predict that as long as people are capable of escape, they try to escape; and panic or other characteristics of behavior are not influential factors. The chart shown in Fig. 2.1 (obtained from [7]), shows the relationship between mobility, complexity of the architecture and people's reaction to fire. This chart indicates how, unless forced to, people do not defend in place or try to find refuge. It also confirms the preference for familiarity (of a refuge) to staying in place and defending against the fire. The fact that people always try to escape and rarely seek shelter even in the case of extreme smoke has been confirmed by Kobes et al. [12].

However, it is important to note that flight behavior is not equivalent to competitive behavior characterized by pushing and shoving. The competitive behavior, which is central to the first two models listed above, has been established to be non-existent during egress, at least not in the sense of it spreading through the crowd. Cocking and Drury [28], who are the main proponents of the self categoriza-

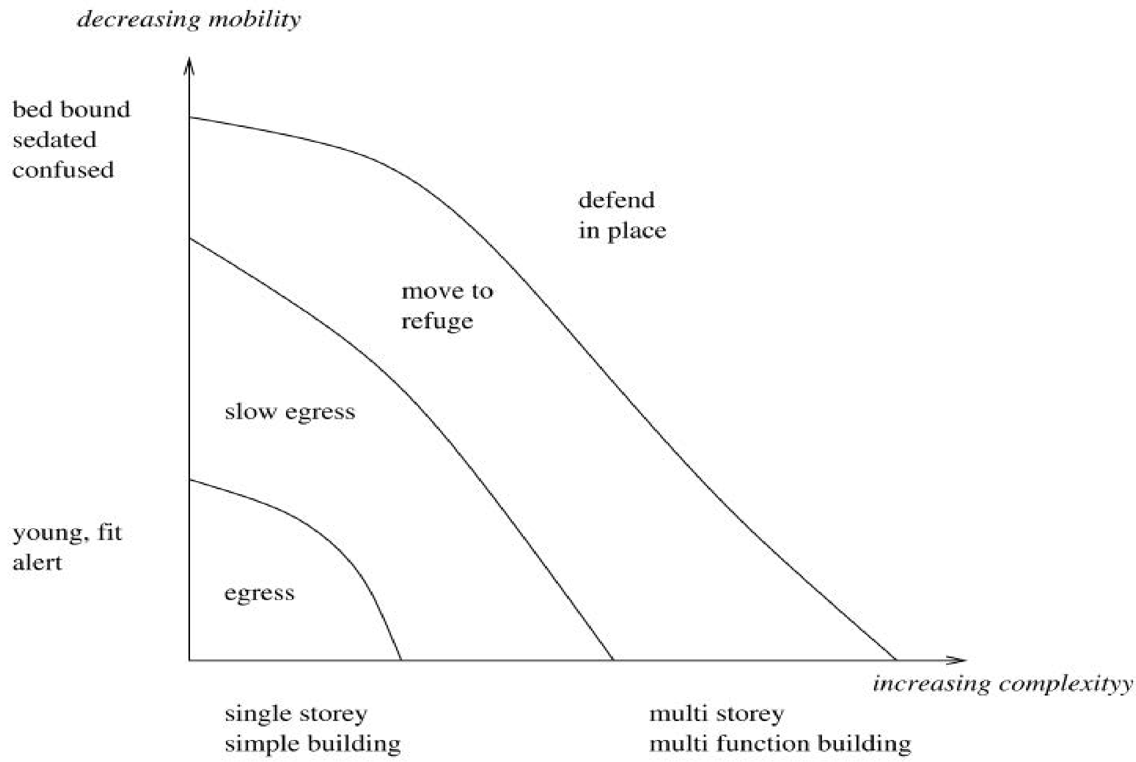


Figure 2.1: According to this chart from [7] there are four strategies that humans resort to in egress. Studies have shown though that more often than not, egress or slow egress are the only strategies taken.

tion theory, do admit that individual panic does occur; but rather than the panic spreading through the crowd it is the calm people who manage to impose their will on other people and calm the people who panic. The same thoughts were echoed in other studies [13, 15, 16]. Several studies [15, 16, 41] actually take a much stronger stand that competitive behavior almost never happens and rather people almost always behave altruistically. This was further confirmed by Torres [9] who found that individual competitive behavior never occurred. Nevertheless, people did do whatever they could to enhance their and their groups survival but without knowingly causing harm to others (which is what competitive behavior/ panic entails).

A further point in favor of the latter four models is the importance that they give to social bonds. For example [22, 43, 44], among others, have already demonstrated the important role that familiarity plays in behavior during egress. This was reaffirmed by Torres [9], who found that even in cases of extreme danger, people still maintained their social bonds. In fact, as opposed to the non-social model, in the real life evacuation, social bonds never broke down. If people did manage to get out of the fire, they would try to come back or help their trapped group members in some way [9, 12].

The normative model, affiliative model and the SCT models also recognize the importance of social roles in determining the reactions of people to fire. Many studies [15, 23, 29, 32, 33, 39] recognize this. They explain how the employees of a workplace who are trained or prepared, generally try to guide customers to the closest exits. They also indicate that within groups, the leader or caregiver (e.g. teachers or parents leading children) continue to take role of leaders during egress and try to find a safe evacuation path and try to protect their group.

In summary, most experiments and studies have been in favor of an affiliative or SCT based model with certain elements of the normative model included. Thus, the consensus is that people always try to escape while trying not to compete with each other and they look for familiar people or locations in dangerous situations and if possible they even form new bonds with strangers stuck in similar situations. Also, the social role of a person determines his behavior. The staff of a place try to ensure safe egress of customers and social leaders (parents, teachers, etc.) take more responsibility during these times. One of the salient features of a news report of a fire incident or an evacuation of any sort is the irrational and panicking crowd which is discussed in the next section.

2.2.3 On the rationality of crowds

It has been proved [9, 12–16] that very rarely do people panic and behave irrationally in spite of time constraints and stress. However, situations have been observed where people do not take the best possible actions and do not act in their best interests [23].This is probably because people's rational thinking is bounded by the constraints of their knowledge of the environment i.e. they are only bounded rational. Bounded rationality is an idea that is becoming increasingly popular in behavioral economics and it implies three major things [45]:

1. People do not know everything.
2. People cannot think infinitely into the future. They think in the short term and tend to take decisions that benefit them in the short term.
3. People are generally loss averse i.e. they do not like to take a risk of loosing more even if the gains are much higher. In a fire evacuation this means that people avoid action for small problems and take drastic actions as things get out of control. This is because early action might result in huge losses [35].

If they are only bounded rational and they tend to make worse decisions as the fire gets worse, then it implies that the time pressure and stress must play some part. Ozel [17] proposed a decision making theory which explains this. The basic premise of his theory is that given the same set of information, people may attend to information differently depending on the stress and amount of time pressure they experience. When people gain information they feel less stressed. This can also explain why people investigate and try to gain more information when they perceive the first few ambiguous cues of fire.

One of the significant ideas suggested by Ozel [17] that could be key to creating an accurate model of egress is the idea of filtration. According to this, to cope with time pressure and unavoidable conditions, people try to filter out all the cues that they deem as unimportant or less important. The rate of this filtration increases as the time pressure increases and as a result cue utilization decreases. This in turn implies that they have lesser information about the environment and tend to behave less rationally. This effect has also been observed by Davis et al. [46] in older people who, due to age, are only able to process less information. The significance of information in egress and more particularly perception will be explained in more detail in Chapter 4.

Thus it is understood that humans act rationally within the bounds of their knowledge. However, as the situation worsens, their behavior tends to look more irrational to an observer. This is because the evacuees observe less on being stressed and as a result have lesser knowledge; This in turn results in, what appears to be, irrational actions.

2.2.4 Summary

To summarize this section, some of the important features that characterize an egress are:

- Ambiguous Cues: most cues are ambiguous in nature and they need to be present for a certain period of time before catching someone's attention enough for them to even start investigating.

- Early investigative behavior: Early movement is characterized by investigation rather than egress. The investigators then gain knowledge or information either from what they observe directly or from what they hear from others. So there is a *spread of information* in the environment [37, 47].

- Flight behavior: Once people interpret the situation as fire, they react to it by trying to get out of the building. They do not try to fight the fire or to seek shelter unless they are forced to by the circumstances.

- Search for familiarity: People's first action while trying escape is to move around and try to find their primary group members who they are familiar with. They then try to exit through some exit that they are familiar with rather than observing new signs. The search for familiarity, also implies the importance of groups and social bonds, to the extent that even after exiting the building, people might come back to help people from their group.

- Absence of competitive behavior: People do not engage in competitively pushing or shoving others when engaging in egress. The rare cases when pushing or shoving occurs, it is because the individual involved is forced to do so.

- Altruistic behavior is common: People tend to help others who need help. They also do not panic or act irrationally. Instead, they follow social norms and try to be as orderly as possible.

- Decisions and behaviors are dynamic: As people interact with the environment and the other people in the crowd their decisions and behavior might change or be influenced.

- Bounded Rationality: Stress and time constraints cause a reduction in cue utilization and information availability and thus cause people to make decisions that with complete information will seem irrational.

In this section the behavior of humans during fire evacuations has been presented and the factors discussed has been summarized above. In the next section, some of the computation models that have been developed over the years are presented. These models are analyzed against the understanding of human behavior that has been presented in this section.

2.3 Computational Models of Egress

Conducting experiments and analysing an environment or an event for it's safeness can be expensive and, more importantly, quite dangerous. Through modeling and simulation, it might be possible to prevent the unnecessary loss of life. It can help architects design buildings better and the management and fire fighters to handle situations better. To be of most use, these models have to be able to accurately simulate how humans behave. A good predictive model can also help test the existing theories of human behavior through the study of emergent behavior. In the previous section the reader was introduced to psychology and sociology literature on how humans and crowds behave in fire and other evacuation scenarios. In this section, computational models of egress that have been developed over the years will be introduced. Section 2.3.1 introduces the different components that generally constitute a computation model of egress. Section 2.3.2 presents a broad overview of the different kinds of modelling approaches along with some of their strengths and weaknesses. Finally, Section 2.3.3 explains in more detail some selected models.

2.3.1 Components of a computational model of egress

Depending on the purpose of the model, the approach used and the level of detail, a model can consist of various components and sub-components. At the most basic level each model will have: a model of the environment and a model of individuals involved.

2.3.1.1 A model of the environment

Most models have an environmental model that represents the physical environment of the location where egress is taking place. They may be continuous or discrete and generally consider a single floor with passageways seperated by walls. Doors are almost never modelled. At a lower level, depending on the scale of the simulation, in room obstacles like pillars or furniture are also sometimes simulated. Some models do consider multi storey environments. However, movement along staircases and escalators is more complicated and generally ignored except in rare cases [48**?**].

An important point of difference is generally the resolution of the environment. Coarse network models have entire rooms as their smallest entity and cannot predict within room complexities of movement, while others have fine networks, which can predict within room movements through the division of the rooms themselves into fine grids. Even this minor approximation is avoided in models that use continuous space. These models can thus model the entire complexity of motion and interaction between the evacuees.

It is also useful to have some model of how the fire or smoke will spread within the environment. In some cases, this can be done by creating a separate external model of the fire or smoke and importing it for the simulation or it can be done in the same model and simulated in parallel with the model of egress. Olenick and Carpenter's report [49] gives a compilation of different models that are used for modeling and simulating fires. In general, however, calculating smoke spread in a simulation is computationally expensive and is not often done.

2.3.1.2 A model of the individuals engaging in egress

This is the most important part of the model and there are a wide variety of ways in which this is done. These will be discussed in more detail in Section 2.3.2 and Section 2.3.3. 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. This is discussed in much detail in [2, 50]. 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 like in [50, 51]. 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. This is also extensively discussed in some surveys [36, 47].

- 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 and this is discussed in more detail in Chapter 7. Movement during egress can have complications because of the effects of fire and smoke on visibility and following behavior [12, 52?].

- Knowledge: Knowledge can refer to either knowledge of events or knowledge of the environment/ layout. Most models assume complete knowledge of both. However, there are some that do model individual specific knowledge and exchange of information. These will be discussed in more detail later.

- Behavior and decision making capacity: This refers to the detail in which some of the behavior mentioned in Sect. 2.2.4 is modeled. This also refers to the social interactions that takes place between the evacuees. Some models do not consider behavior at all, while others have sophisticated models of decision and behavior. The same behavior can sometimes be produced by using different techniques. Some models use a functional analogy, like social forces, which approximate behavior through mathematical formulas. While others use rule based techniques.

- A model of trained staff: It is generally recognized that the employees of a place or the people trained in handling a fire evacuation have a key role to play during egress [8, 15, 22, 29]. Some models do take this into account. Recently, there have also been computational models studying the effect of signboard on evacuation.

In the following sections, some of the different approaches that are used for modeling crowd evacuation is presented. Not all models have all the components mentioned above, but most models have at least a few of them.

2.3.2 An overview of existing computational models

There are a lot of reviews of computational models of egress. Some [13, 53–56] list and attempt to categorize existing models according to their properties. The literature review in Still's thesis [2] and Santos and Aguirre's article [8] give comparisons and critical analyses of some of the most popular computation models of crowd egress. The former gives an analysis from a computational perspective while the latter analyses the models from a psychological perspective. Together they form an invaluable source of information on computational models and their strengths and shortcomings.

The different behavioral criteria along which computation models can be differentiated are discussed in some surveys [54, 55]. Others [13, 56] give a comparison of the models based on an engineer's or a modeler's perspective. It gives an idea of the computational complexity of each of these models. Schadschneider et al. [13]

explained strengths and weaknesses of each approach in more detail, while [56] lists the different models of each kind and their features.

As mentioned in Section 2.1, all these differences can broadly be said to be differences in level of detail. At the most abstract level, we have models that have a coarse network of just rooms connected to other rooms and homogeneous uniform crowd behaving like a fluid. At the most detailed level, we could have an agent based model that considers each individual to be different from every other and with each having its own memory, decision making capacity and behavior, all of which are in turn influenced by their interaction with other people in the group.

In the following pages, some of the typical models of each approach are introduced and analyzed with respect to the discussion in Section 2.2.4.

2.3.2.1 Network or Queuing Theory based approaches

These approaches use the coarse network approach mentioned earlier. Nodes are used to represent rooms and passageways and generally any place which can hold people. The arcs in the network represent the gateways or connections through which people move from one node to the other.

One of the earliest models of this kind is Evacnet+ [57]. In this model, the user specifies the capacity and initial content for each node and the traversal time and arc flow capacity of each arc. Queuing theory is then used to calculate the time required to evacuate the building. As in other networks, waiting time, throughput, length and utilization of each arc can also be determined. [58] is another example of a similar queuing theory based approach which has a basic ability to show heterogeneity. But this ability is very limited because there is no way that grouping behavior, investigative behavior or effect of time and stress can be modeled. More importantly they do not correspond to a tangible reality [59]. [60] is another example of this approach.

2.3.2.2 Flow models

In these models the crowd is assumed to be a fluid and the crowd motion is predicted based on the geographical layout density and velocity of the particles. Schadschneider et al. [13] provided an excellent analysis of these kinds of models. The first of these models was Henderson's model [61] according to which the interactions between the pedestrians were calculated using the kinetic theory of gases. One of the theory's main drawbacks was the assumption of energy conservation and Newton's third law being applicable to crowds.

These drawbacks were removed in later models which make use a of a density function. This function was derived from Boltzmann's transport equation that describes the change for a given state as the difference of inflow and outflow due to binary collisions. These later models are also able to distinguish between different groups of particles that had different destinations. These models however fail to work at low densities and cannot model the complex heterogeneity of a crowd [59].

2.3.2.3 Environment Control Based Models

These models are more complex than the above two and generally manage to model some complexity of behavior. The idea behind these models [62] is that it will be computationally difficult to model a very large environment with a large number of people, each of them instilled with some complex decision making and behavioral ability. So rather than model complex entities, the decision making ability and "behavior" of the agents are stored in the environment itself. The location of an agent determines its behavior. Thus, these models can be termed to as being controlled by the environment.

Banerjee et al. [62, 63] propose an environment with various different layers that together store all the information that is needed for the simulation. This reduces the complexity of the agents considerably. The idea of using environments for computation with the agents having limited complexity is one of the oldest and most established in the field of modeling and simulation. Cellular Automation models and lattice gas models have been around for a long time, and a majority of the models of these kinds use what can be termed as *environment control* to implement complex behavior:

2.3.2.3.1 Cellular Automata based approaches: A Cellular Automation (CA) model is one in which space and time are discrete. The state space of a CA model is also discrete and finite. In each time step the values of all cells are updated synchronously based on the values of cells in their neighborhoods. Depending on the type of neighborhood (i.e., von Neumann, Moore), and the type of lattice (triangular, square, hexagonal, etc.), the exact number of cells in the neighborhood of a given cell can vary [**?**].

This technique is very popular and has been used in a number of different ways. In [54, 55] these models are called *fine network models*. [**?**] is a typical, simple CA model in which the agent position is updated based on its distance to each possible exit and the density of the crowd at each possible exit. People choosing familiar exits and choosing to stay with their groups is also modeled. However, they use it only for single room evacuation.

One of the drawbacks of a typical CA model like this is that movement is very simple in that they can only move to one of the fixed neighboring cells which are present at fixed angles. This is very limiting when trying to model detailed motion. In [**?**] a real coded cellular automata model is proposed. It is called a real coded cellular automata because of its proposed ability to consider velocities at angles other than multiples of 45 and magnitudes more than a single cell length away (non discrete velocities). Each time a points location ends up at a point other than one of the grid points, it is assigned one of the 4 neighboring points probabilistically. Some approaches [?] use a hexagonal grid layout instead of square cells. This gives more freedom of motion.

In [?] slightly more heterogeneity can be modeled since each agent can have a different velocity. Though it is just a movement model, the pre-evacuation time is modeled through the use of a delay parameter specified for each agent. The same thesis suggests that by combining a CA model with a network based model, these models can be used for modeling egress from complicated buildings also.

Most simple CA based models tend to concentrate on movement. As a result most of these models lack any complex behavior simulation.

2.3.2.3.2 Lattice gas models: Lattice gas models are CA models that make use of a discretized version of the Boltzmann transport equation to model motion [64? ?]. They make use of a discretized version of the Boltzmann transport equation for modeling motion. These models do not generally model any complex behavior. In fact they are generally used on a very small scale to study patterns of egress from a single room and to study the effect of different obstacles, number of exits, etc. on egress in extremely dense environments. The approach is not appropriate for modeling behavior.

2.3.2.3.3 Floor field models: Floor field models are more complicated CA models that are more capable because agents can send messages between each other and communicate.

The Extended Floor Field Model [?] in which agents interact through virtual traces that act like the pheromones in chemotaxis and the SWARM information model [65] which uses multiple floor fields to model transmission of knowledge between agents are typical examples of floor field models. In the SWARM information model, there are multiple static fields on the floor to indicate the different world views. A higher number indicates a more accurate model. At certain points (for example, points where maps are displayed), the agent can upgrade its knowledge to a more accurate model. It also models communication at a basic level. When an agent with a higher index comes in contact with one with lower index, then the lower agent's index is upgraded. Thus it has a basic method of communication and exchange of information. [?] is also a similar model that has a static potential field guiding towards the goal and a dynamically generated interaction field.

The Situated Cellular Automata (SCA) modeling framework [66] was proposed so that floor field models can be extended to model more complicated behavior by psychologists and sociologists based on their findings. The authors call it a multi-agent systems based approach, but most of the calculation and processing is done by the environment and not the agents, hence we call this also a environment control based model. Each agent in this model has a particular state that he is in, which influences the way he acts. The idea is to allow agents to emit and store messages in specific locations. When agents reach a particular location they react to all the messages present there (some from other agents, others from the environment). In this way communication and group behavior can be modeled effectively.

While similar models (especially the SCA model) might, in the future, be extended to model complicated high level behavior of the kind mentioned in Section 2.2.4 it is not a very intuitive approach. It is more natural for people to think of behavior at an individual level. Programming behavior through an environment requires abstractions that are difficult for all but the most experienced modellers. Due to this limitation it might be difficult for psychologists or sociologists, who are not used to computational models to extend this model effectively.

2.3.2.4 Agent based approaches

Agent Based Modelling is the preferred approach for modeling complex behavior [67–69] because the bottom up approach makes it easier to view and break down problems into more manageable entities. What exactly are agents? Woolridge [**?**] defines agents as a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its design objectives. He further defines Intelligent agents as those agents that are capable of flexible autonomous action through reactivity, pro-activity and social ability. The agent architecture is the software architecture used for modeling this decision making ability. Specifying an architecture would provide a structure that can be used to break down the complicated process of decision making. There are several frameworks like the Belief-Desire-Intention (BDI) framework [**?**] and the Recognition Primed Decision (RPD) that provide a structure on which agent based architectures can be developed.

For example, [70] is a NetLogo based agent based simulation while modeled the effect of *management* and trained staff. This is done by programming officer agents that instruct other agents to leave and give them instructions on how to do the same. This is a relatively simple task in agent based modeling; models that simulate more complicated emotions, behavior, social interaction and decision making are discussed in more detail in Section 2.3.3.

2.3.2.5 Hybrid approaches

Most models use one of these different approaches or can be classified into one of these. However, there are certain exceptions that can't easily be classified as any of these. For example, the pedestrian motion model proposed in [59] is a multi agent model that uses a cellular automata at the lowest level for collision avoidance. In fact, it is not even a simple CA model, because it uses a network based representation for path finding and a radial individual specific discretization of space to capture decisions about the direction of walking and the aforementioned CA layer at the bottommost layer.

2.3.3 Detailed Discussion of Significant Computational Models

The previous section introduced some of the popular approaches to crowd simulation. In this section, models that manage to simulate some of the key characteristics explained in Section 2.2.4 are introduced.

2.3.3.1 Pires's model of pre-evacuation behavior

Unlike the other models that are described in this section, Pires's model [18] is not a complete model of egress behavior. Nevertheless, it is important because it proposes a method by which the pre-evacuation decision making of an individual can be simulated using a simple Bayesian Belief Network (BBN). It also takes into the consideration the effect of time constraints and stress on the BBN.

However, this approach has its limitations. Most of the details of the pre-evacuation behavior are abstracted away as probabilities which are estimated by *experts*. So, besides not being able to simulate the effect of different kinds of cues, this model does not make it easy to analyze and understand the behavior and movement produced.

2.3.3.2 Legion

Still's Legion model [2] is based on extensive analysis of crowds exiting stadiums in the UK. The Legion model was extended from the Vegas Model, which worked on the basis of an extensive set of rules that governed the behavior of each agent. Such an approach, Still found, had two basic flaws:

- One cannot determine, a priori, all the possible conditions that can possibly occur. The same person might have different reactions on different days. As a result, a lot of these specific rules and conditions could be replaced by noise.
- A lot of behavior can actually emerge due to the self organization of the system, without actually specifying these rules.

Still realized that it would be impractical to consider a parameter for smoke, another for nature of threat, another for the emergency and so forth. According to him, during an emergency, a human either moves towards the threat (investigate), stays in place (ignore) or moves away from the threat (evacuate). This choice is based on the value of three parameters that interact- Objective (try to move to desired or intended end point), Motility (try to maintain optimal velocity) and Constraint (try to maintain a minimum distance between yourself and the other objects)- and one parameter that represents the reaction time- Assimilation (delay in reading and reacting to the environment). He has explained how all the key factors in an evacuation, for example, communication, alertness, social role, position, effect of location, population density and so forth, can all be modeled using just these four factors.

The model is notable for presenting various studies to accurately model the size and shape of human beings. But it comes to the conclusion that a square cell will most accurately model a human being considering the possible ways in which he can turn. Others [50, 51], however, have shown that an elliptic or a tri-circle model of humans would be more accurate.

Still uses environment control, through what he calls iSpace, for modeling communication between agents. As mentioned in Section 2.3.2.3, this approach reduces computational complexity, but at the cost of realistically modeling communication between agents. While groups or clusters do emerge in the model, this is solely the emergent behavior from movement and it is not related to primary groups or particular entities. The perception model is also quite simple and the idea of knowledge spread is not modeled. As a result, even though the idea of emergent behavior is captured brilliantly in this model and a lot of emergent natural phenomena are obtained, it fails to consider pre-evacuation behavior, partial knowledge and the search for familiarity.

The greatest strength of this model lies in the importance given to data, both for theorizing and validation. Also, the physical model used, which was based on an extensive study of the existing data, is something to be emulated. Most importantly, the idea of emergent behavior in crowds was emphasized by the model and experiments. His adherence to Occam's razor in keeping the model as simple as possible and letting more complicated behavior emerge from this is a further strength of this model.

2.3.3.3 MACES + PMFServ

This model [24] is most notable for the approach taken to modeling complex behavior. In order to obtain believable emergent behavior a popular psychological model of human beings (PMFServ) was integrated into their existing Crowd Simulation System (MACES).

The original MACES model was a multi-agent system based model, with each agent having its own representation of the map. Through exploration and communication they create a more detailed view of the world. This, combined with a model of leadership and non leadership behavior, formed the high level decision making which gave a destination to the lower level path planning algorithm. The lower level path planning algorithm used Helbing's social force model [71] for collision avoidance. This is one of the few models which takes into consideration the partial knowledge of occupants. However, it is assumed that once informed about a room, the agent memorizes and never forgets it. Agents explore in a depth first manner if a path is not known.

PMFserv was conceived as a software system that would expose a large library of well-established and data-grounded Performance Moderator Functions (PMFs) and Human Behavior Representations for use by cognitive architectures deployed in a variety of simulation environments. Its principal feature is a model of decision-making based on emotional subjective utility constrained by stress and physiology. The basis for this decision making model is Maslov's hierarchy of needs [72] and the OCC model [73]. Needs reservoirs corresponding to the degree to which the agent has satisfied his needs are set based on any action that might have occurred in between decision cycles. The OCC model describes a hierarchy that classifies 22 emotion types. Using this hierarchy, the mood of a person in a particular situation can be determined. Besides PMFServ, there are other approaches to emotion modeling for agents as well. For example, appraisal theory based approaches are also used in certain Agent Based Models [25].

In summary, in this architecture, PMFServ provides the emotional and behavioral basis which is utilized by MACES for motion. Though it has a model of behavior, emotions and decision making it does not model pre evacuation behavior or the search for familiarity. However, it is still of interest to us because of the model of partial knowledge and the idea of having a dedicated and extensible module for behavior with an extensive database of emotions and their effects on decision making. This sort of extensibility is very useful for a behavior model of crowds. In fact, a crowd simulation framework should be flexible enough that different theories of behavior can be used without too much effort. However, one drawback of the architecture used here is that emotions and behavior have no effect on the lower level social forces model. This is a natural difficulty of this approach of improving the model by integrating another existing model instead of having a single central model.

2.3.3.4 Collective Panic Behavior Model

França et al. [27], created a simulation model of panic behavior which was based on the hysterical belief theory explained in Section 2.2.2. To recap, this theory believes that people normally follow social norms and behaviors. A fire alarm or smoke causes social unrest. Following this, people start investigating and communicating with each other and start forming a consensus about what this threat represents. This process of interaction is called *milling*. Following this, a stage of collective excitement is reached wherein a *collective belief (CB)* is formed between the people and the people no longer have an individual thinking capacity. Next, a social contagion stage is reached wherein the CB is highly contagious and spreads to other people who come in contact with this crowd. After a short period of time, this situation escalates into collective panic where none of the actions of the crowd can be accurately predicted because they are believed to behave irrationally.

Most aspects of this theory of panic have been proven to be wrong as explained in Section 2.2. Nevertheless, this model is still interesting due to the detailed way in which the behavior model has been converted into a computation model. Also, the agent architecture is notable for the possibilities it holds for extension.

Each agent is made up of four modules: a Belief and Knowledge Management Module (BKMM), a Perturbation Module (PM), Dissipation Module (DM) and Social Cognitive Module (SCM). The environment itself is divided into three parts: a physical environment, a communication environment and a group mind representation.

- The PM is responsible for picking up cues from the communication environment and analyzing these. These cues are first semantically analyzed using rules specified in the BKMM to determine the mood of the message (loving, aggressive, neutral). Once analyzed, the information is stored in the BKMM as either a belief or as knowledge based on the amount of evidence for this belief.

- On obtaining evidence, beliefs may be changed to knowledge. The knowledge base has three parts to it: The first represents the intrinsic features of the agent (e.g. health, speed), the second represents the knowledge that it gains through perception (e.g. Temperature) and the third represents social state variables that are determined by its interaction with other agents (susceptibility to other agents). The BKMM also has a rule base that stores information on how to behave and act and interpret information. The rule base itself has three parts: a functional part which gives the agent an identity and goals and instructions to pursue them. A Dynamics module which relies on learning and a reactive module related to the agent's survival which is usually time-constrained. There is a micro representation of the CB in each agent. According to the crowd theory used, there is a tendency for this belief to move towards the macro CB.

- Social Cognitive Module is like the control unit of each agent. This module again consists of three parts: Firstly, it has a Cognitive Core module (CogC) that continuously processes and manages information and guides actions so that the agent can pursue and fulfill its goals. An event that poses a threat triggers the Collective behavior core to take over. This makes the agent act in a collective manner. The trigger is done based on experiences stored in the memory of the agent. Uncertainty about information, due to only partial knowledge, triggers social unrest and milling. During this process, the agent builds up its micro CB representation. As the panic rises, the dynamic rules become less important. The knowledge base has a variable for permissiveness, which represents the adequacy of the actions of the group to the situation. When the actions cross a threshold, i.e. they are inadequate for the situation, collective excitement results. At this point, even the functional rules start playing and social norms start being broken. After a certain point, this situation escalates into panic and all the agents act according to the macro CB which enforces a competitive behavior among the agents. The third part of the SCM called communication core is responsible for dispatching instructions from the CogC or CBC to the dissipation module through a queue.

- The DM is responsible for sending messages into the environment in the correct format according to the Agent Communication Language. It does so on getting instructions from the SCM and adds details to the message like the mood of the message and whether the information is conveyed as a gesture or a speech.

Detailed communication between agents is possible through the use of ACL with details of mood and the type of gesture. Agents don't directly exchange information. Instead, the communicating agent dissipates the message into the environment; and autonomous agents check the communication environment in order to check whether the message is relevant for reaching its goal. The BKMM module represents the idea of information processing and uncertainty reduction accurately. However, the theory of panic and collective behavior, on which the model is based, is much debated [9, 10].

Combined with the PM, a model similar to this can in theory be used for modeling all the pre-evacuation behavior that is necessary. While it is possible to make all these extensions, it doesn't seem like the authors have attempted to do this in their model. Also there is no group behavior or search for affiliation. This is expected because the Hysterical Belief approach on which the model is based has no concept of social bonds and their importance). The absence of altruistic behavior and the importance given to competitive behavior are some other drawbacks. The major drawback, however, is the lack of details about the physical model of the agents or the environment or the level of detail used.

2.3.3.5 Exodus

Exodus [74] is one of the most detailed and mature evacuation simulation tools available. It has different packages for building, maritime and aircraft environments. The buildingExodus model comprises five core interacting sub-models: these are the occupant, movement, behavior, toxicity and hazard sub models (see Fig. 2.2).

Once the building layout is specified as either a DXF file, CAD package, or by using the interactive tools provided in the suite, it is converted into a spatial grid representation which stores all the details of the building including obstacles present inside it. It is also able to store and show movement at staircases and across multiple levels. The grid itself is represented as a graph with the nodes representing a small region of space and each arc representing the distance between each node. Individuals

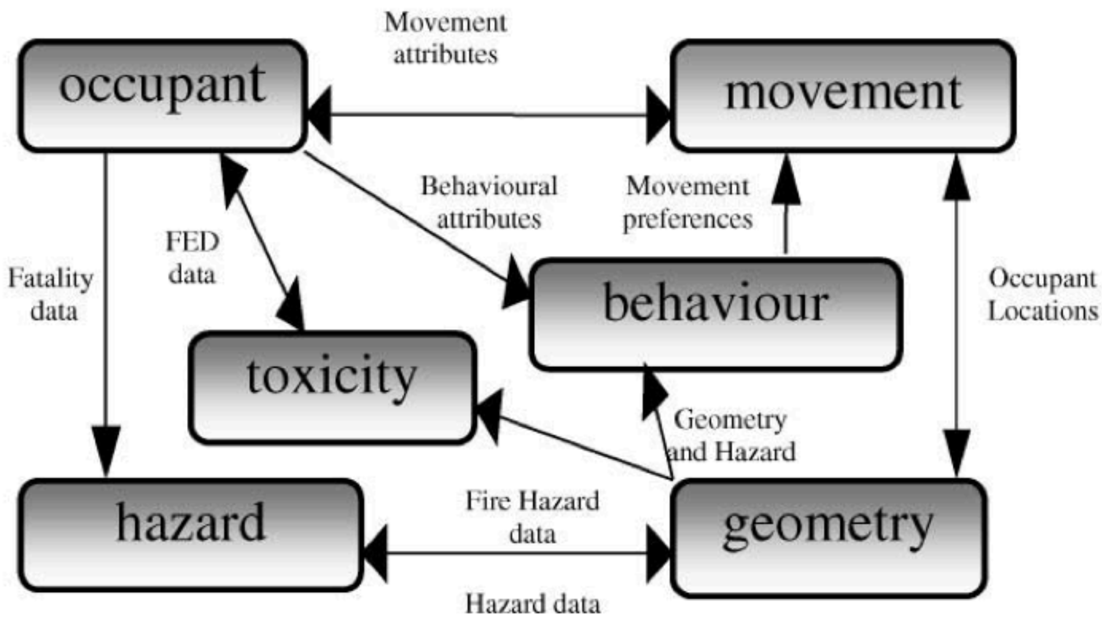


Figure 2.2: Interaction of EXODUS modules [75].

travel from node to node along the arcs.

Each individual has more than 20 behavioral attributes that are specified at the start of the simulation and stored in the occupant submodule. Based on these, the behavioral module determines the behavior of the agents. Two kinds of behavior are modeled: *normal* behavior and *extreme* behavior. The only difference between the two is that in extreme behavior, the agents have a patience threshold beyond which they will stop queuing and resort to some other course of action. The behavior model works on two layers: a global layer and a local layer. The global layer gives a set of waypoints or a single destination (possibly the exit or a familiar location). The local behavior is determined by the agent's attributes and determines factors like how long he waits before evacuating, conflict resolution and other things. Some of these factors and local behavior are probabilistically determined.

The toxicity submodule determines the physiological impact of the environment on the occupant. This submodule assumes that the effect of smoke or fire is determined by the dose received and not the exposure concentration. The toxicity affects the occupant's mobility agility and travel rates. The hazard module on the other hand is responsible for generating hazards like smoke and fire in the environment as a function of time and location. A dedicated zonal fire simulation model called CFAST is used for this purpose. Several analytics tools have also been developed to analyze the results produced by the simulations.

Gwynne et al. [75] added some new features including the ability to specify occupant specific knowledge of the layout of the building. The behavior module is further modified so that the agent chooses to use emergency exits that he knows of only when he is showing extreme behavior. This representation of a map of the place rather than just a path to exit allows the occupant to dynamically re-plan his route. He is also given the ability to learn from signs and through interactions with other agents.

The effect of smoke is also modeled by reducing the efficiency of the path selected and reducing the speed of movement as per the concentration of the smoke. This reduction in efficiency and speed happens only as long as the exit is not visible to the evacuee. A certain inertia in route replanning is also modeled to indicate the reluctance that people have in changing their pre-decided route.

Hollmann et al. [76] presented a theoretical prototype of an emotional model that modeled the effect of time pressure and stress on evacuees was introduced into buildingEXODUS. Each agent is specified by giving a list of tasks or waypoints that he has to visit before or during the evacuation. The tasks are categorized as being compulsory time critical and elective and each of them are given an estimated time for completion. An urgency factor indicates how constrained for time the agent perceives itself to be. The speed, drive, patience and the itinerary of each agent is rearranged based on the elapsed time, time left and the feelings of the person. Without an actual implementation of the prototype, it is difficult to analyze the strengths and weaknesses the proposed emotional model.

The strength of the model is the fact that it has a dedicated fire/ smoke simulation engine and a toxicity calculation module. The prototype of the emotion model to be used is also an innovative addition. The ability to specify so many parameters and thus the heterogeneity of agents is also important, as is the ability to model complex building layouts and obstacles in a variety of ways. Nevertheless, the model falls short on a few key factors. It does not try to model crowd behavior or its effects. The idea of cue perception and pre-evacuation behavior is very limited, unless the user specifies a list of tasks that each occupant is to do [74]. However, the theoretical prototype fordoing this was never implemented and tested.

The current behavior model is quite limited, with new flowcharts and algorithms and new sets of rules required for each new situation. As discussed earlier, this excessive dependence on specific rules specified is generally considered to be a bad approach [2].

2.3.3.6 ESCAPES

ESCAPES [77] is a multi agent based evacuation simulation software tailor-made for airport environments. Unlike most of the other models mentioned earlier, it also has a 3D visualization engine, which makes it more usable for security purposes for non experts. One of the ways in which this model improves on others is that it can model families and social bonds. It models how evacuees search for their family members before attempting to evacuate. Family members also communicate all their knowledge to other family members. It also models a fear factor and emotional contagion. The knowledge of the fire spreads and the authority figures are able to calm people down. The model also takes into consideration the incomplete knowledge of most people and the spread of knowledge in the environment. However, the models for these are simplistic with only 2-3 states of fear, emotion and knowledge. The reaction time is modeled as a function of the proximity to the event. Agents that are near an event evacuate immediately, whereas others, will behave normally until they get enough information to know that they need to exit.

While the model includes some behavior like affiliation (within families), the prevalence of competitive behavior in the model is unrealistic. The family sizes are fixed (Parents and two children) and the only social bonds that exist are within this family. The model of partial knowledge is rather simplistic as is the investigative behavior model. Despite these drawbacks, this is one of the few models that consider almost all the factors discussed in Section 2.2.4.

2.3.3.7 MASSEgress

Pan's [26] multi agent based model of evacuation called MASSEgress is notable for the well structured and detailed architecture of the agents used and the importance that he gives to non-adaptive behavior being synonymous with a high stress evacuation environment.

Mobility, age, gender and body dimension are the only intrinsic characters that are included. A population generator is used to generate the required distribution of people based on these factors. The simulation uses a grid based physical environment which can be loaded as a CAD file. The data from simulation is logged to facilitate easy analysis, and a 2D and 3D visualization engine is also implemented for ease of use and simple analysis. The simulation engine itself simulates the behavior by dividing it into three parts: a perception engine, a behavior engine and a motor engine.

The perception model used is relatively complicated compared to the models discussed above. It consists of a point test method and a ray tracing algorithm implemented along with a visual cone. The visual cone specifies the region in which the agent can perceive and is determined by the eye position, viewing angle and visual range of the agents. The point test algorithm determines whether an exit or waypoint is perceived. The ray tracing algorithm determines which of the obstacles are perceived and ensures that only objects closest to the agent are perceived.

The agent behavior is considered to happen at three levels: an individual level, a group level and a crowd level. At the individual level, an agent generally acts using his experience. If experience can't help then they act rationally within the limits of their knowledge. If they are too stressed, then they start acting on instinct. Instinct refers to competitive behavior where pushing, jumping out of windows and fleeing towards very crowded, blocked exits take place. At the interaction level, a social identity based model is used. Each agent has a social identity and each social identity has a set of actions associated with it. Depending on the situation, the actions taken by an agent are determined by the social identity. Pan assumes that during an extremely stressful situation people forget about their social roles. Personal spaces are defined for each individual which they always try to maintain. If this space is violated, they get agitated and stressed and will eventually lead to *non-adaptive behavior*. The model also assumes a strong herding behavior, where the first reactors influence the reaction of the rest. At the crowd level, the three factors that influence the behavior of an agent are crowd density, environment constraints and perceived emotion and tension. The first two factors are standard in most crowd simulation environments. The third factor is interesting, it states how the individual's perception of a system as stressful determines how stressed he is, not just what happens to him. So even in a non emergency situation, *non-adaptive behavior* might occur if a false alarm or some other stressful situation arises. Queuing, competitive, leader following, altruistic and herding behavior are modeled as resulting from the interaction of these different factors. A decision tree is used to simulate this behavior and to show how each of these behaviors is caused as a result of the aforementioned three levels. The actual implementation of the behavior at an individual level consists of 5 factors: familiarity (memory), decision making type (the intrinsic factors determined decision tree), urge to exit, stress threshold type and herding factor.

The movement engine has a simple collision detection algorithm and controls basic movements. Basic movement on stairways are also modeled.

The greatest strength of this model is the way in which the higher level behavior of agents are determined and described using a few fundamental lower level behaviors. It also has a more detailed visual perception system and movement system. However, it does not model pre-evacuation behavior or affiliative behavior of any sort. Like some of the other models, there is an undue prominence of non-adaptive behavior during evacuation.

2.3.4 Summary

In this section, the different types of computational models of fires ranging from network based models to smart environments and agent based models were introduced. Seven existing models that model the key features highlighted in Section 2.2.4 were also presented and analyzed.

- Pires's model [18] was one of the earliest to consider pre-evacuation behavior. However, the model abstracted away details of the pre-evacuation behavior as probabilities making it more difficult to study and analyse pre-evacuation behavior.

- Still's thesis [2] highlighted the importance of data. He also, importantly, highlighted the fact it is not necessary to have a complicated model to simulate complex systems. Rather, simple rules may be able to produce the required complex behavior. Models should where possible follow Occam's razor, i.e. the simplest rules should be used. This was exemplified by Pan's MASSEgress model [78] which produced higher level herding, following and competitive behavior by using simple lower level rules.

- Pelechano's work [24] in combining a dedicated behavior model (PMFServ) with their existing crowd simulation model (MACES) demonstrated the importance of inter-disciplinary collaboration. By integrating an existing detailed emotion model to improve an existing computational model, they demonstrated the strengths and limitations of this approach.

- The Collective Panic Behavior Model [27] demonstrated how a theory of human behavior can be computationally modeled without having to make any abstractions.

- The EXODUS model [74] is one of the most detailed and mature models today. Hence, it is an excellent source of information on egress modeling and simulation.

- ESCAPES model [77] is significant for the importance given to modeling affiliative behavior and the spread of information.

2.4 Summary of Literature Review

This chapter first introduced the complexity of the problem of modeling crowd evacuation and its multidisciplinary nature. In Section 2.2, the current theories on crowd behavior during an evacuation were presented with a summary of the salient features required in a comprehensive model of evacuation behavior. Section 2.2.4 summarized the salient features of human behavior during fire evacuations. In the following section, the different approaches to modeling crowds was introduced and some of the more significant models were presented in detail. Their strengths and shortcoming were summarized in Section 2.3.4.

Despite the number and variety of models available, they all have certain common shortcomings. This chapter has provided a broad look at the computational models of egress and briefly mentioned some of their strenghts and weaknesses. In the following chapter the IBEVAC agent architecture that modularizes the different behavioral components of an agent simulating human behavior. This architecture is used to identify the key problems of existing computational models.

Chapter 3

The Building Blocks of Crowd Behavior During Egress

In the previous chapter, the salient features of the behavior of a crowd engaging in egress were introduced. It is understood that people don't immediately exit a building on hearing a fire alarm or seeing smoke. The occupant gets only an inkling about the danger that is possible. In both these cases there is not enough information for him to get scared and make the decision to egress. If the cues are interesting enough, he then embarks on investigating to gather more information. On realizing that the situation requires some action, he forms a plan to evacuate either alone or, if possible, with his primary group members. In forming this plan of evacuation, unless he is trained for egress or very familiar with the environment, it is unlikely that he will have knowledge of all exits. As a result, he is most likely to just move to the nearest *known* exit. An overview of this process of human evacuation is illustrated in Fig. 3.1.

Section 3.1 explores how a small set of core subprocesses and their interaction is necessary and sufficient to produce this evacuation process. Section **??** introduces some of the shortcomings of existing models of each of the current approaches to modelling these sub processes. Section **??** explains how these shortcomings are addressed and overviews the key contributions of this thesis.

3.1 The Building Blocks of the Egress Process

The individual behevaior of an evacuee during emergency egress was summarized above from the literature discussed in Chapter 2. This section outlines the building blocks of a system that simulates crowd egress during an emergency event. The first step in simulating the behavior of any human being engaging in an activity is modelling his *perception* of the environment. Once perceived, the information gained from perception is used to *identify events* and trigger key actions. In the case of an egress simulation, this would be evacuation (or one of the processes leading up to it). Following this, the person tries to form an evacuation plan using the *knowledge* he

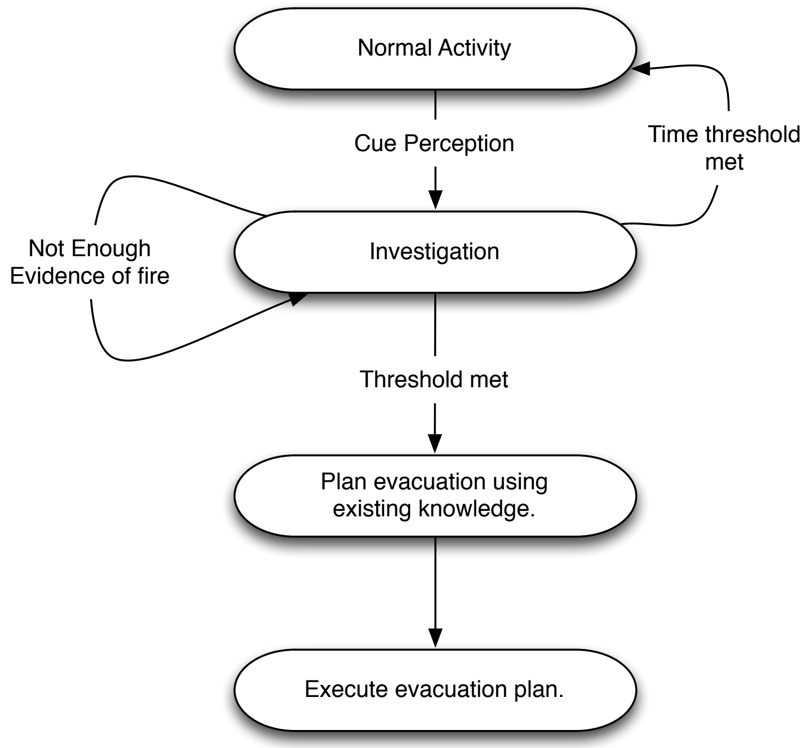


Figure 3.1: The Process of Evacuation: This state diagram shows the different phases of behavior of a person engaging in egress and the triggers that cause phase changes

has of the layout of the environment and also the information that he is currently perceiving. Once such a plan is formed, a *path is planned* towards this point and he moves along this path towards his goal. Thus the process of egress simulation can be said to consist of four major building blocks: perception, event identification, a knowledge model and navigation. The following sections defines and explains each of these building blocks and their significance in the evacuation process.

3.1.1 Perception

Perception refers to the process by which an environment is observed by a person. For an agent, this implies that it should extract features from the environment. These features are called percepts [79]. Each percept gives the evacuee certain information about the environment. At the simplest level, percepts provide the agent information about the location and the environment around it and thus allows it move naturally around the environment. In some cases, something out of the ordinary like a ringing fire alarm or smoke or even people running away from a location, might be perceived. Communication between agents can also be considered to be a mode of perception since it is a process by which additional information is gained by the agents. The perception process is the main interface of the agent with the environment through which it gets all the information needed to act. In order to act on information perceived, it is essential for the agent to be able to identify events that require some action.

3.1.2 Event identification

In some cases, evacuees might perceive something out of the ordinary like a ringing fire alarm or smoke or even people running away from a location. If these special percepts, known as *cues*, are intriguing enough, then the occupant will set about investigating the environment in search of more cues that would help make a decision on a plan of action.. Cues are certain changes in the environment that indicate that something is wrong or different from normal [16]. Thus, cues help people identify an event and a need for an action. During emergency egress, on perceiving *sufficient* cues from the environment, an evacuee stops whatever task he's doing and initiates a process of investigation. Once enough evidence is gathered to convince the evacuee of danger, evacuation starts; if there is not enough information then the evacuee will likely resume their previous task. Thus identification of events is a key component of the evacuation process that is especially important for modeling pre-evacuation behavior.

In summary, event identification is the process by which the evacuee interprets perceived information and decides to proceed to the next phase of evacuation. Executing the action for a particular phase generally requires the evacuee to proceed to a particular location in the environment. This is done using the subjective knowledge that he has of the environment.

3.1.3 The knowledge model

On recognizing that there is an event to escape from, the evacuee moves towards the closest known exit. Each evacuee holds his own personal version of the map of the environment which is used for evacuation and movement in general. This personal map is called his cognitive map [?]. In most cases, this map is not complete. In a scenario where all known exits are blocked or if the evacuee does not know any exit, he is likely to engage in some sort of exploration behavior which helps increase his knowledge and improve his cognitive map.

The process of knowledge modelling encompasses how the cognitive map is modelled and how it is obtained by the evacuee and his actions when insufficient knowledge is available to act. Modelling evacuee-specific *knowledge* is necessary to model the heterogeneity in behavior found in real life emergency evacuations. The key function of the knowledge model for the agent is to provide it with a target to move to complete the action required based on the event identified. The actual movement towards this point is controlled by the navigation system.

3.1.4 Navigation

Navigation is defined as the process or activity of accurately ascertaining one's position and planning and following a route. In the context of egress simulation, we define navigation as the process by which an evacuee first plans his route towards a *goal location* based on his cognitive map and then moves along this route towards the goal. Thus, Navigation consists of 2 distinct processes: planning a route and following the route. The former is referred to as path planning and the latter is called motion planning.

During emergency egress, once evacuation has started, the agent decides that it must proceed to a particular exit, say exit D. Given the current location and this goal, the path planning system recommends a sequence of locations, or waypoints, through which the agent should proceed to get to this goal. Understanding the process of path planning in agent based simulations is easier if it is divided into two parts: A higher level path finder that finds abstract logical waypoints towards the goal, i.e. go through room A to room B to room C and take Exit D; and a lower level mechanism that translates these logical waypoints to physical locations on the map that the agent can pass through to reach it's goal. Fig. 3.2, which gives a mathematical overview of the navigation process, refers to the former as "Logical Waypoint Determination" and the latter as "Current Waypoint Path Determination". Once these physical waypoints are determined the actual movement towards these locations are determined by the motion planning process.

Motion planning is a term borrowed from robotics which originally means detailing a task into discrete motions. In the context of crowd simulation, we use the term motion planning to refer to the task of finding a collision free velocity to get from the current point to the next waypoint in the planned path. The motion planning layer ensures that the agent manages to reach its next way point without colliding with other agents.

Assuming that the cognitive map is modelled as a graph with the edges E representing *areas* or rooms in the environment, Figure 4.1 gives a mathematical model of how navigation is generally modelled.

The goal position ($g^{x,y}$) is first received by the *Logical Waypoint Determination* (WD) system which then uses a route finding algorithm like A-star or Djikstra's to find a set of logical waypoints (E_i) that will lead the agent from its current position($p^{x,y}$) to the goal position ($g^{x,y}$). The logical waypoints in the path so planned will be a list of links from the agent's cognitive map ($Env_{cognitive}$). This implies two things: Firstly, it looks at the environment at the room/ area level. Secondly, the agent plans a path according to his personal cognitive map hence there is no garantuee that the path planned by two agents from the same point will be exactly the same. This step is called a waypoint determination step because it returns a set of logical waypoints to be used by the agent to reach its goal. This set of logical waypoints is then passed to the next level of navigation, i.e. *the Current Waypoint Path Determination* step.

The *Current Waypoint Path Determination* (PD) differs from the higher

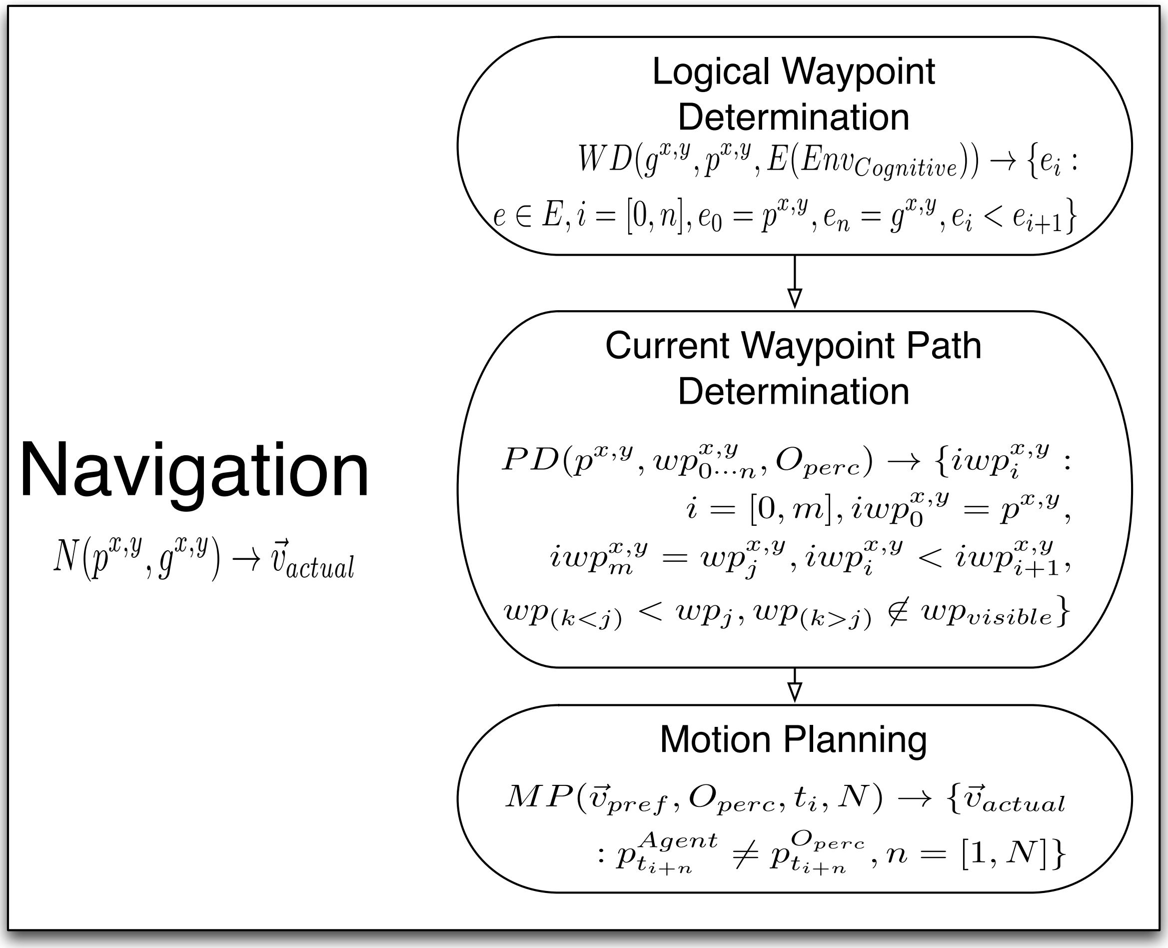


Figure 3.2: Mathematical description of the working of a Navigation System

layer in that it takes into consideration dynamic obstacles i.e. other agents, as well as the static obstacles to determine a collision free path from the current location to the farthest visible waypoint. The logical waypoints are first converted to a set of concrete waypoints ($WP^{x,y}$) which are actual locations on the map. Using the set of perceived obstacles (O_{perc}) a set of intermediate waypoints ($IWP^{x,y}$) that would enable a collision free path to the farthest visible concrete waypoint ($wp^{x,y}_j$) is calculated and passed to the next level. This level can also be referred to as the *strategic planning step* since it tries to model how a person strategically moves from one point to another while ensuring that it minimizes collisions with others. Nan's pattern based approach [81] and ClearPath by Guy et al. [82] are examples of models for this layer.

The preferred velocity of the agent is then set to the velocity that would lead it to the next intermediate concrete waypoint. Following this, the Motion Planning System like RVO [83, 84] or Social force [71] based methods determine the actual movement of the agent for the next time step of the simulation based on this prefered velocity. At each time step (t_i), the motion planning system take a preferred velocity ($\vec{v}_{pref}$) and set of obstacles (O_{perc}) (both static and dynamic) as input and outputs a possible velocity ($\vec{v}_{possible}$) that the agent can use to ensure that collisions do not occur for the next N seconds. The two important points of difference from the

Table 3.1: The Building Blocks of Human Behavior during Egress

Building Block	Definition	Purpose
Perception	The process of gathering information about the environment.	Learn about the environment and observe events.
Event Identification	The process by which the evacuee analyses and aggregates cues and identifies an event.	Change from one phase to another based on perception and internal state.
Knowledge Modellings	The process of using stored knowledge to formulate a plan for evacuation.	Determining a goal based on the current spatial cognitive map.
Navigation	The routing and movement process.	Handles movement towards the evacuee's current goal.

previous layer is that it has some noticeable effect only when a collision is imminent and that it is very short term (limited to a few time steps) as compared to PD.

To summarize, the Navigation system receives a goal that is passed to the highest level which determines a high level route through the different areas in the environment to the goal; this waypoint is passed to the next level which determines a path towards the current waypoint that avoids dynamic obstacles and calculates the velocity of the agent in order to get to the waypoint while avoiding collisions for the next time step of the simulation.

In summary, a perception system along with event identification, a knowledge model and a navigation system can together be used to produce the entire process of a person evacuating from a building. The function of each of these building blocks is summarized in Table 3.1. In the following sections, we first identify shortcomings in existing models of these processes and then explain the contributions of this thesis to those areas.

3.2 Shortcomings in Existing Models

The previous Section identified the core building blocks of an agent based model of emergency egress. In this thesis, the approach taken is to identify key shortcomings in each of these core aspects of agent based simulation of crowds and propose solutions to these. This section briefly describes the shortcomings in existing models and gives an overview of the rest of this thesis.

3.2.1 Perception : the lack of a realistic approach

Perception is the process by which agents perceive and gather information about the world around them. It is thus a crucial part of an agent based simulation of crowds.

However, in most models, it is standard practice to consider a simple circular or elliptical sensor range. All agents and objects within that sensor range are perceived by the agent. One of the rare exceptions to this is the MASSegress model [26] that makes use of a ray tracing algorithm to model perception. The assumptions that an agent can perceive as many objects as are there in the sensor range without any internal limit on capacity [11] and that perception is simply a visual process are both simplistic. Another related consequence of the limited information processing capacity of humans is that the human brain tries to chunk similar information to improve it's efficiency. Modeling this limited information processing capacity and chunking can produce significant improvements in the realism of crowd simulations. This is demonstrated in Chapter 4 which introduces an Information Processing Based Perception model which takes this into account.

3.2.2 Event identification: modeling pre-evacuation behavior

Several studies [21] have shown that humans do not evacuate immediately on hearing a fire alarm. In fact, the delay between hearing the alarm and actual evacuation starting can be as long as 15 minutes in some cases [**?**]. This can have significant results on the time to evacuation and the general efficiency of evacuation. However, despite several studies highlighting this, pre-evacuation behavior is hardly ever modeled. In the few instances were it is considered [**?**], the models are rather simplistic.

Chapter 5 introduces a model for event identification that enables the modeling of pre-evacuation behavior and studying of its effects. Through simulation of certain scenarios, the importance and usefulness of modeling pre-evacuation behavior is demonstrated.

3.2.3 Knowledge modeling: the effect of partial knowledge

On deciding to evacuate an evacuee plans a path towards an exit. Ideally, this plan would be to move towards the closest exit that is known. In most cases, however, say a shopping mall or a hospital, it is highly likely that the majority of the occupants do not know emergency exit locations or the closest exits. How evacuees explore and form their memory in such a situation of partial knowledge is still an open problem.

Existing simulations either assume complete knowledge or have a simplistic memory model where a single visit is remembered forever. It is unlikely that evacuees have such eidetic memories. Also, it is common to simply take a depth first approach to exploration in case of incomplete knowledge. However, there is no proof whether this is the actual way in which evacuees explore.

Chapter 6 first introduces a game based methodology for studying exploration of indoor environments and how human memory works during exploration. By comparing against a pure random walker, it is shown that humans are in fact more effective explorers than a random walker but not as efficient as is portrayed in existing computational models of egress. The study also revealed some interesting patterns in the strategies used for exploring complex indoor environments.l

3.2.4 Navigation: analyzing motion planning systems

The motion planning system used in an agent based simulation of egress is a key determinant of the kind of behavior produced by the model. The motion planning system used can have a great impact on the patterns of motion produced and the dynamics of the crowd. There are several different models of motion planning that have been proposed that sometimes work in very different ways. Each model has it's strengths and there are studies that demonstrate their strengths. However, despite the abundance of models, there aren't any standard methods for comparing different models. In Chapter 7 of this thesis, we quantitatively compare and evaluate existing motion planning systems and determine a metric that can be used for differentiating existing motion planning systems and compare their working against real world data.

3.3 Contributions of the Remaining Chapters

Following is a summary of the contributions of the remaining chapters:

- **Chapter 4:** This chapter presents an Information Processing Based model of perception which was presented at the Cyberworlds 2011 Conference [**?**] and further explored in the extended version published in the Transactions on Computational Science [5]. This chapter additionally contains some validation of the model against real world experimental data.

- **Chapter 5:** This chapter presents a method for modelling pre-evacuation behavior in emergency egress simulation. The model was presented as a poster and short paper at the Pedestrian and Evacuation Dynamics Conference in 2012 [**?**].

- **Chapter 6:** A game based methodology for studying the effect of memory on exploration of complex indoor environments and different exploration strategies used is presented in this chapter. A paper highlighting the contributions of this paper has been submitted to Cognitive Science: A Multidisciplinary Journal.

- **Chapter 7:** The final contribution of this thesis is a methodology for quantitatively comparing different motion planning systems which was also used to compare some popular models against real world data. These findings were published in European Physica Journal B [**?**].

3.4 Summary

This chapter first summarized the behavior of an evacuee during evacuation from the literature in the previous Chapter. Following this, the four essential building blocks for an agent based simulation of emergency egress was presented. Following this, shortcomings of existing approaches to modeling these parts were identified and the contributions of the remaining chapters was introduced.

Chapter 4

An Information Processing Based Approach Perception Modelling

[1]

A model of perception is a core component of any behavior model for egress simulation. This chapter introduces a novel agent based approach to modeling perception that takes into consideration the limitations of human perception.

Agent-Based Models (ABMs) consist of large-numbers of heterogeneous, autonomous entities inhabiting a spatially explicit, partially observable environment; macro level dynamics are said to emerge through the asynchronous interactions among these entities [67, 68]. Each of these individual entities will iterate through a sense-think-act cycle, where agents obtain information from their environment through *sensing*, make a decision through *thinking* and finally carry out their decision by *acting*. In many application areas in which ABMs have been applied, including crowd simulation, the emphasis is generally on describing thought processes accurately via rules. However, sensing is a critical aspect in the modeling process and can greatly impact both the individual and emergent properties of the system.

The terms perception and sensing are often used interchangeably in simulation literature. For clarity in explanation, the term *perception* is used to define the complete process of obtaining a set of (possibly filtered) *percepts* [79] from the environment. *Sensing*, on the other hand, is defined as the process of obtaining raw information from the environment; in this definition, and in this model, sensing is a part of perception.

The sense-think-act cycle is the process by which humans get information from the environment, process this information and finally, act based on the decision made. Rather than what a human sees, hears or smells, what is more important is what he can mentally process. In fact, the entire human perception system can simply be considered to be an information processing entity. In this chapter a

[1] This chapter was presented at the Cyberworlds 2011 Conference [?] and further explored in the extended version published in the Transactions on Computational Science [5]. This chapter additionally contains some validation of the model against real world experimental data.

perception systembased on this idea that perception is the process of gathering information from the environment is presented. This is called an *Information Based Perception*(IBP) system.

Miller's seminal work [11] on human cognition revealed two important characteristics of human cognition: 1. Humans constantly group together similar data into *chunks* of information. 2. At any given time, a human can only process a limited amount of information. For IBP, the assumption is made that this limited capacity results in humans being attracted towards certain kinds of information, e.g. a bright light or a celebrity; this, in turn, results in other information in the environment being unnoticed. By organizing information into chunks, humans are able to use their limited information processing capability more efficiently. This ability can manifest itself in different ways. It can be reasonably assumed that during motion planning, humans will process a group of people coming towards them as a single obstacle rather than many individuals. This grouping not only helps the person make use of his limited information processing capacity more efficiently, it also helps him conform to social norms that instruct him that walking through a group of interacting people would be rude.

This chapter explains and illustrates the working and usefulness of an Information Based Perception system for agents. Its viability is demonstrated through the implementation of a simple moving agent and by incorporating information based processing into the agent's motion planning system. Why motion planning only? Besides being one of the major components of Agent Based Crowd Simulation, motion planning is also a process in which the effects of using a new perception system can be observed easily. The experiments towards the end of this chapter illustrate the significant effects that a modified sensing and perception system can have on an existing *motion planning* algorithm. The results produced are also compared against real world experiments to demonstrate that the results produced are realistic.

The remainder of this chapter is organized as follows: Section 4.1 gives some background on how humans perceive the world around them; the IBP model itself is introduced in Section 4.3; following this, Section 4.2 presents an analyses some of the existing work in motion planning; in Section 4.4 presents the work done in visual, experimental and quantitative validation; finally, Section 4.5 concludes this chapter and gives an overview of the work that needs to be done.

4.1 Limits of Human Perception

In 1953, Hochberg and McAllister [85] proposed their theory humans try to group together similar information so that information can be encoded in the simplest possible format. They call this *the simplicity principle*. This idea was further extended by Miller [11] originally proposed the idea that, at any given time, humans can only process a limited amount of information. He explained this as the human short term working memory having a limited capacity. Humans are aware of what is in their short term working memory and they aren't aware of what isn't stored in it. To enable humans to store more information in this limited storage space, humans "chunk" together similar information. He originally proposed that the short term working memory could hold 7 ± 2 chunks. Recently, Cowan [86] has argued that this limit is actually 4 ± 1 for most humans. Thus, even though a person's 5 senses are giving him a constant stream of information about the world, limitations of human short term working memory force the person to act on the basis of only a fraction of this received information.

But then, which specific fraction of this received information is cognitively processed? Regarding visual perception, some studies [87–89] have shown that humans only pay attention to certain salient features in the objects that they see. This results in them not noticing changes in items that are not of interest to them. O'Reagan et al. [88] classified elements as either central interest or marginal interest elements and prove that the internal representation of the visual world is rather sparse and essentially contains only central interest information and not information of objects of marginal interest. The world that we perceive around is a combination of this sparse visual world along with the information in our working short term memory received from our other senses.

Based on these studies, for our model, we make the reasonable assumption that the human brain uses some mechanism to determine the significance of a particular *raw percept*. And the short term working memory stores the most significant information in its limited capacity. It is important to realize that this significance determination is done for *all* information received, regardless of the source. We call this significance, the *amount of information*.

The idea of considering the human perception system as an information processing system is not unprecedented. Broadbent [90] extensively discussed the idea of using information theory for modeling human perception. Various studies were presented that indicate that humans have an upper bound on their capacity for holding information for perception. For a single dimension, this limit is roughly estimated to be about 5-6 percepts. For more than one dimension, the number of discernible alternatives is larger but not as large as would be expected if each dimension was completely independent.

The idea of humans being able to process only a limited amount of information is not new to computer animation either. Hill [91] was one of the first to introduce the importance of cognition in sensing. Courty [92] used a saliency map based approach and Kim et al. [93] used cost-benefit analysis in a decision theory based approach to determining the interest points. Grillon and Thallman [94] automated this process of interest point determination. They used criteria like proximity, relative speed, relative orientation and periphery to determine the interestingness of various features.

The majority of existing perception systems, consider perception to be only visual perception. Even in more detailed crowd simulation systems like LEGION [2] and MASSEgress [26] perception is implemented to aid movement by detecting other obstacles and goals to enable planning a path towards the goal and to provide a collision free motion. The simplified IBP System implemented and demonstrated in this chapter is similarly limited, i.e. the IBP is modeled in the context of collision avoidance. The information which the agents perceive are dynamic obstacles, i.e. other agents or groups of agents. However, in theory, the concept of an information processing based perception system can be extended to include factors like cue perception as explained in Chapter 4.

In the present model, it is not proposed to model all the complexities of human perception and visual cognition, rather an agent based perception model for crowds is presented which can not only show a basic implementation of the idea of information based perception but can be easily extended when required, to model more complicated visual cognition. In order to demonstrate the effect of IBP on an agent's motion planning system. It is first necessary to have an idea of existing motion planning systems.

4.2 A Brief Introduction to Motion Planning Systems

To recap, navigation is defined as the process or activity of accurately ascertaining one's position and planning and following a route. Thus we use the term *navigation* to refer to the complete process of how a person moves from one point to another. Navigation itself can be broadly divided into 3 (or 4 parts) as shown in Fig. 4.1. In this section, a brief overview of *motion planning* is given. A more detailed description and analysis is given in Chapter 7. In a simulation, motion planning ensures that the simulated human does not go through another human being in the crowd.

There are various different approaches to motion planning. For example, Okazaki and Matsushita [95] used a magnetism based approach to motion with all agents having the same pole so that they repel each other and the goal having the opposite pole. Klein and Köster [?] used a similar approach of using coulombic charges instead of magnetic poles; they assigned positive charges to goals and negative charges to obstacles and agents. In this section, only two of the most popular models for motion planning and collision avoidance used in agent based models, viz. the Social Forces model and the Reciprocal Velocity Obstacle (RVO) model are presented.

The social forces model was first introduced in Helbing's paper [71]. In this model, each agent is modeled as a particle that has multiple forces acting on it.

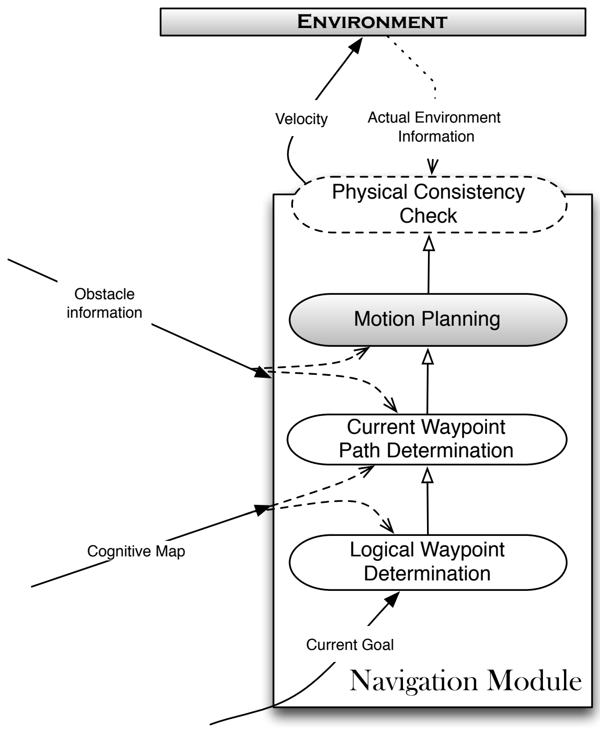


Figure 4.1: Navigation Architecture

Repulsive forces help in collision avoidance and attractive forces model goal directed and grouping behavior. Over the years, this model has been extended and combined with other higher level behavior models. For example, in [96] more complicated group movement was modeled with an underlying social forces model for collision avoidance. In his thesis, Still [2] criticized the heavily mathematical approach which, according to him, is too complicated to be the natural way in which humans try to avoid crowds.

Another ABM that is increasingly becoming popular for collision avoidance is based on the idea of using the relative motion of objects to determine their time to collision. A velocity is then selected which maximizes this time. This algorithm, based on RVO was first extended for use with multi agent systems in [97]. Since then there have been several modifications and improvements to the system but the underlying algorithm still remained the same. CLEARPATH [82] which mathematically optimized RVO was the first to introduce a change in the underlying algorithm. Guy et al. [83] introduced an entirely new approach to RVO that was based on computational geometry and linear programming. This method further improved the efficiency and smoothness of the system and was called *RVO2*. In another article, Guy et al. [6] introduced a personal space factor and an observation delay making the algorithm more appropriate for virtual humans.

Guy et al. [6] introduced an extension to RVO in the form of a higher level navigation based on the principle of least effort. While it is obvious that rational humans would prefer taking the path of least effort, as was explained in Section 4.1, humans do not have perfect knowledge or perfect calculation. Also, it is arguable whether humans are always rational enough to choose least effort as their goal.

There are a number of existing motion planning methods that can effectively and efficiently calculate trajectories that avoid all collisions for agents, even in relatively dense environments. For robots and computer games, this might be the ideal goal: perfect, smooth and efficient motion. However, for applications like simulation of emergency evacuation the goal is obtaining realistic motion and not smooth and efficient motion. While humans thrive to be mechanically efficient, this is hardly always the case. There exist, among other things, social norms and limits to mental processing capabilities that prevent individuals from following their ideal preferred path. Also, humans do not necessarily use optimality (in any sense) to determine their preferred path. The approach presented here is a more naturalistic one [**?**] in that the author feels that motion planning models should explicitly consider and model human inadequacies and limitations.

In this chapter two additions to general motion planning algorithms are proposed: 1. Group sensing for motion planning which results in agents avoiding clusters of other agents when choosing their collision free path. 2. Filtering of percepts based on the amount of information provided to model limited information processing capabilities of human beings.

Another important optimization that was introduced by Guy et al. [6] was using the idea of clustering very distant objects into KD-trees to reduce computational cost. While this might sound similar to the idea that is suggested in this chapter, there are two fundamental reasons why this is different from the algorithm presented here: Firstly, the present model uses multiple levels of clustering which will be explained in more detail in Sect. 4.3.1. Secondly, the motivation and hence design is significantly different: clustering in IBP is used as a reflection of how agents perceive their environment and not an optimization for collision avoidance.

In the following section a method that will emulate how humans perceive groups whenever possible and a system in which the agents avoid these groups rather than individuals is proposed. This has been done using the Evolving Clustering Method (ECM) [98] and computational geometry based RVO2 [99]. But our approach can, in principle, use almost any clustering and collision avoidance algorithms.

4.3 The Information Based Perception Model

This section explains the Information Based Perception System. Figure 4.2 illustrates how motion planning works in an agent in terms of a sense-think-act cycle. An agent's perception can be described by a function $f : Env \to p*$, where $p*$ is the set of percepts. Each percept p is then processed by the agent in its decision making process, which in turn will determine an appropriate action for collision avoidance. In our case, the motion planning module is passed a set of percepts which consists of

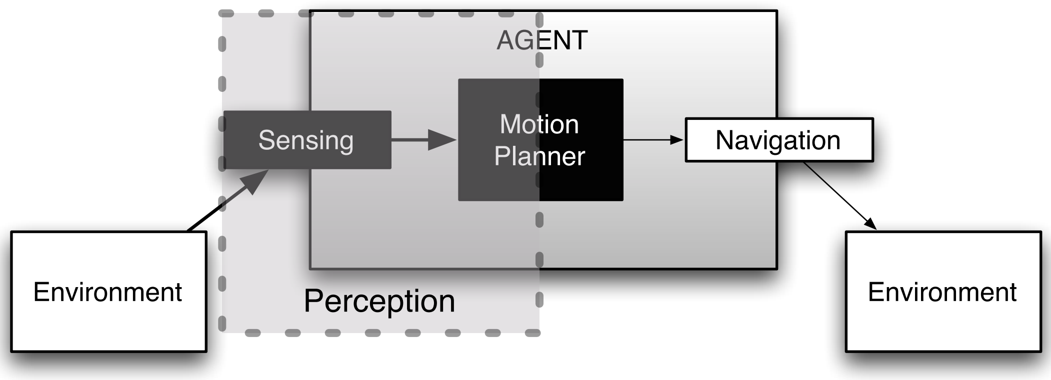


Figure 4.2: An agent perceives and then acts

neighboring agents and static obstacles which it processes to find the most appropriate velocity for reaching the goal. Typically, this list of neighbors is a set of agents within some cone of vision or some distance away from the agent. In the proposed IBP, a modification to this traditional perception procedure is proposed such that it takes place in three phases: clustering, sensing and filtering. Figure 4.3 gives an overview of the process that is detailed in the following sections.

4.3.1 Clustering

Central to our information based perception system is the definition of *information units*. In traditional crowd simulation each individual agent or obstacle is considered as a percept, i.e. as an entity which should be processed by the motion planning system. The first assumption of our approach is that percepts can be both individuals and groups of other pedestrians. Whether an individual considers a group or individual is related to the *coherence* of the group and also the distance of the perceiving agent from the group. In order to achieve this, we perform a global clustering across the entire environment of agents. We create n_l layers within the environment, each layer identifies and stores groups of a particular size, with increasing layer numbers storing groups of increasing size. The criteria which determines what actually constitutes a group is itself unknown and probably highly dependent on the individual. We make the assumption that only the proximity of the individuals to one another determine whether a collection of people is perceived as a *group*.

For reasons of efficiency we simplify things by performing a single clustering (for each level) for all agents at every time-step, the consequence is that we are implicitly assuming all agents have the same notion of what constitutes a group. In reality this assumption may be too strong, different people may have different criteria for what they perceive as groups.

While there are various clustering techniques that could be used for grouping agents, we chose to use ECM [98] because: 1. It does not require the number of clusters to be predefined and 2. It can restrict the maximum radius of a cluster. It

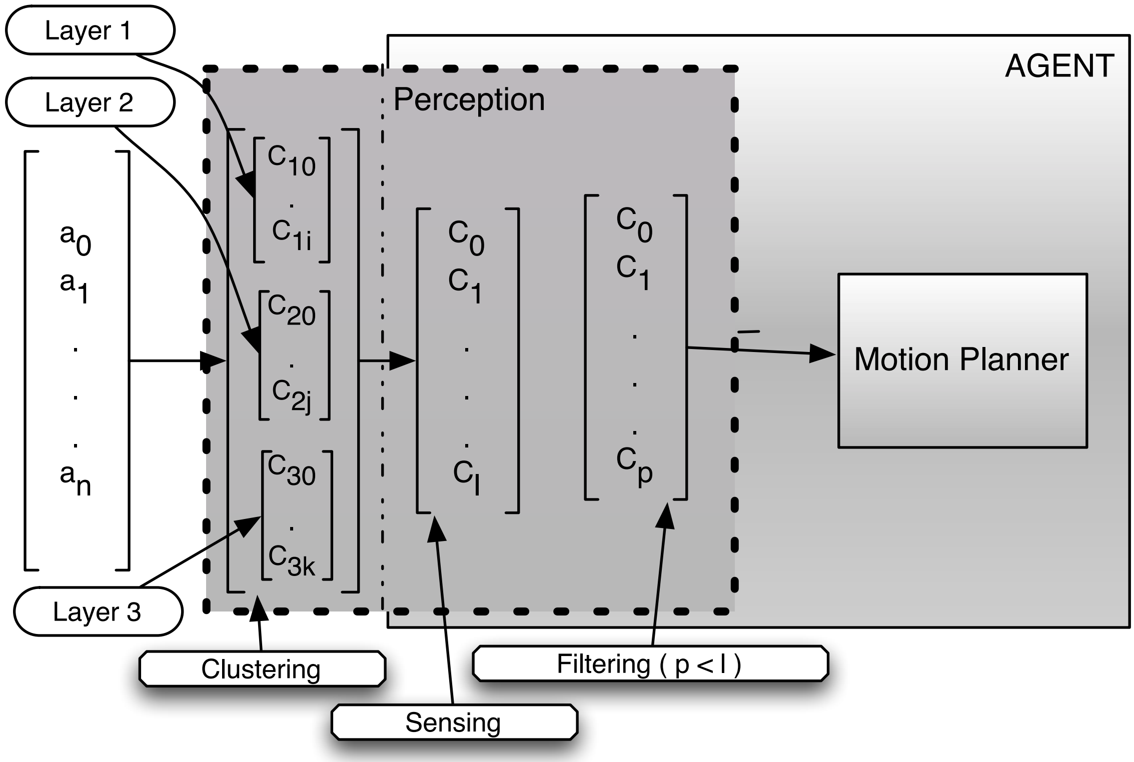


Figure 4.3: Perception in agents takes place through three stages: (1)Clustering is done at a global level. The dotted line indicates this separation. (2) Sensing is the process by which the Agents perceive only a subset of this (3) Filtering further reduces the size of this list and models human visual cognition

is also important to remember that this clustering is done dynamically at *each step* and not as a one time calculation of groups.

First the number of clustering layers is decided. In Fig. 4.4, we illustrate information based perception using two layers. The algorithm starts by initializing a single agent as the first cluster, the maximum clustering radius for layer i, r^i_{max} is fixed (Equations 4.3 and 4.4). Each subsequent agent is then compared with every existing cluster to assess its suitability for addition to that cluster. Suitability is determined by the distance of the agent from the cluster. If the agent lies within an existing cluster, it is simply added to that cluster without updating either the radius or the cluster center. Otherwise, the cluster whose center is closest to the agent is determined. If the agent can be added to this cluster, without exceeding the maximum allowed radius for the cluster, then the agent is added to the cluster and the cluster's radius, center and velocity are updated. On the other hand, if adding the agent violates the maximum radius criteria, then a new cluster is created at the location of the agent.

Once this process is completed for layer i, the process is repeated for layer $i+1$ until the clusters for all the layers are determined. This process is illustrated figuratively in Fig. 4.3. The clustering function for layer i, cf_i allocates one and only one cluster for each agent in each later. This can be represented mathematically as shown below:

$$\forall a_k \in A\ \exists j \in [1, m] \quad cf_i : a_k \rightarrow C_{ij} \text{ where } 1 \leq m \leq n \tag{4.1}$$

$$\forall a_j \in A \quad C_{0j} = a_j \tag{4.2}$$

$$r^1_{max} = 2\alpha * r_a \tag{4.3}$$

$$\forall i \geq 2 \quad r^i_{max} = 2\alpha * r^{i-1}_{max} \tag{4.4}$$

Here r_a is the average radius of an agent[2] in A which is the set of all agents; C_{ij} indicates cluster j in layer i; m is the number of clusters and n is the number of agents. α is a parameter that determines the size of clusters and the range of each region (Fig. 4.4). Through experimentation we found the most pleasing results with $\alpha = 2$.

The ECM based clustering for each layer considers each agent exactly once so it the process has an asymptotic complexity of O(n^2). At the end of each clustering, each agent belongs to a cluster. However, in the absence of nearby agents this might be a singleton cluster.

To correct certain undesirable behavior produced by ECM clustering, a modification was made to the algorithm. With large values of r_{max}, there is a chance that distant agents might be grouped into sparse clusters. To counter this problem, we define a *checking circle* as a circle of radius $2\alpha r_a$. If there are no agents within this checking circle, then the cluster is considered sparse and the cluster is removed. The sparseness check is done five times: First with the checking circle centered at the center of the cluster; and subsequently with the checking circles centered at a distance equal to half the distance from the center of the cluster along each of the coordinate axes.

4.3.2 Sensing

Once the agents have been clustered, the next step is to make use of these clusters for motion planning. As previously explained, existing motion planning algorithms need a list of nearby agents and obstacles to determine the most appropriate velocity. The sensing module of our proposed perception mechanism uses the set of n_l layers created in the clustering module. The list of things to avoid will now consist of agents, obstacles and groups of agents. This list of nearby objects is now calculated from the

[2]In the experiments at the end of this chapter, it is assumed that all agents have the same radius. Hence, the radius of every agent is the same as the average radius.

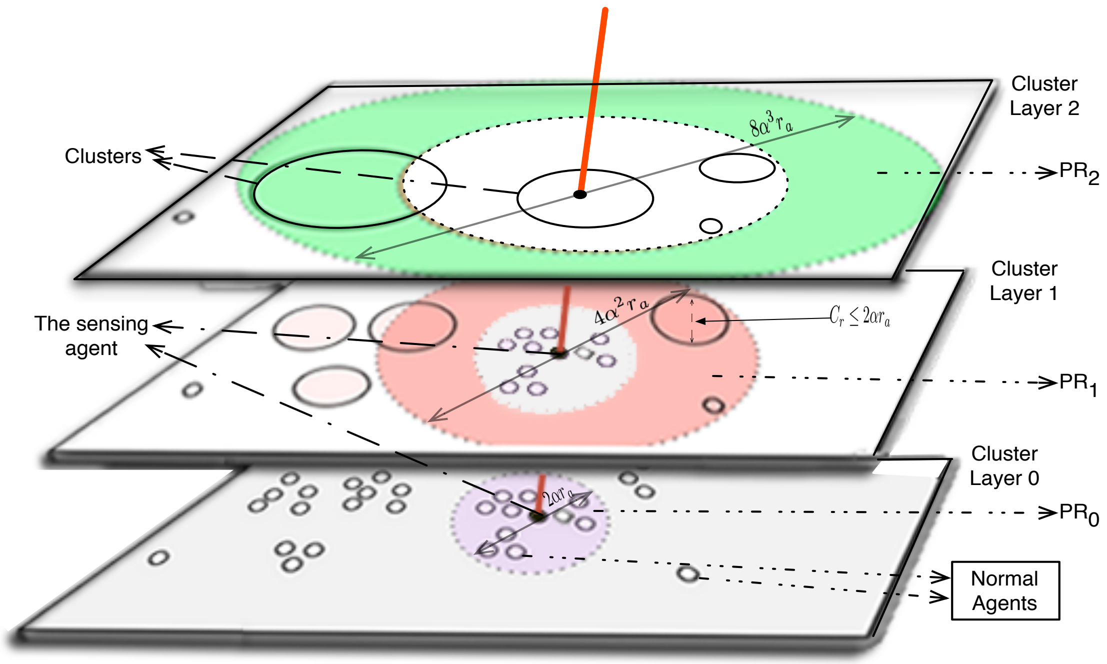


Figure 4.4: The figure illustrates how the opaque agent senses objects using 2 clustering layers. The bottom layer is the original environment and the two planes above show the two clustering layers. Clusters in layer 2 are generally bigger than in layer 1. Solid lined circles indicate the normal agents and the clustered agents. The dotted lines show the regions of perception.

multiple clustering layers as shown in Fig. 4.4.

From each cluster layer (explained in Sect. 4.3.1) a ring shaped *perception region* pr_i is defined for each agent. This region can be considered as a modification of the sensor range which is used in most ABM. In the first region (pr_0), immediately surrounding the agent performing the sensing, the agent perceives other individual agents from the clustering layer 0. This region extends to a distance $r_{pr_0} = 2\alpha * r_a$ from the agent's current location. For each subsequent region, the ring shaped region of sensing is from the boundary of the previous layer's region to the boundary of a circle of radius 2α times the radius of the preceding region. So for region pr_1 the agent perceives groups of maximum size r^1_{max}, as long as the nearest edge of their minimum enclosing circle is within a distance d, such that $r_{pr_0} < d \leq r_{pr_1}$. The result is a list of obstacles which consists of clusters of various sizes and individual agents.

4.3.3 Filtering

As explained in Sect. 4.1, a human being does not cognitively process every single object or obstacle that is within its vision. In other words, an agent can only process a limited amount of information and the information that is processed will be that which is deemed most interesting or important to the agent. So each object in the list obtained from perception is assigned an interestingness score of between 0 and

1 (1.5 for exceptional cases). During the sensing process each agent is given an information limit a_{IL}, indicating the total amount of information that can be processed by the agent. This limit is a parameter than can change as the stress level or other characteristics of the agent changes [17].

For now, it is assumed that interestingness of an object depends on two criteria: 1. The distance of the object from the agent. 2. The angle that the object currently forms with the direction of motion of the agent. A third factor indicating the innate interestingness of the object being perceived can also be used. This can be used to represent a lot of other properties related to interestingness. For example, an object's speed, color, action or something more subjective, i.e. it is of interest only to this agent because of certain properties of the agent. For e.g., for a thirsty agent, a water cooler would be interesting whereas it is unlikely to catch the attention of someone else. A more exact definition of interestingness is not the focus of this report, but the general model here should be able to adapt to more sophisticated definitions. However, a notion of interestingness is required to extend IBP to detect events and cues in the situation and environment.

Based on the two criteria, a score is given to each agent. A distance score of 1.5 is given if the distance between two agents is less than or equal to zero. This is to ensure that in high density scenarios where a collision does occur, a collision recovery mechanism is forced on the objects regardless of what angle or how interesting the object is. For other distances the following equation is used to calculate the score for a distance d. γ and k are parameters which were fixed at 5.0 and 1.11 respectively to get a curve as in Fig. 4.5.

$$S_d = max(min(1.0, e^{\gamma/d} - k), 0.1) \tag{4.5}$$

An angle score of 1.0 is given to all objects forming an angle of less than a_{min} with the agent's direction. For all agents that form an angle of more than a_{max} with the agent's direction, a score of $(1 - \beta)$ is given. For our experiments a β value of 0.9 was used and this is illustrated in Fig. 4.6. For all angles in between, the angle score linearly decreases to $(1 - \beta)$ from 1. This is assigned based on the following equation (Fig. 4.6). All angles are in radians:

$$S_\theta = 1.0 - (\beta * (a - a_{min})/(a_{max} - a_{min})) \tag{4.6}$$

The final score for the object is calculated as the product of the S_θ and S_d (as long as the distance score is not 1.5). This list of objects is then sorted on the basis of the score that is determined. Objects are then removed from the head of this list in turn and added to the final list of perceived objects as long as the cumulative score of all the perceived objects does not exceed the information limit for the agent, a_{IL}. All the remaining objects are dropped from the list of objects

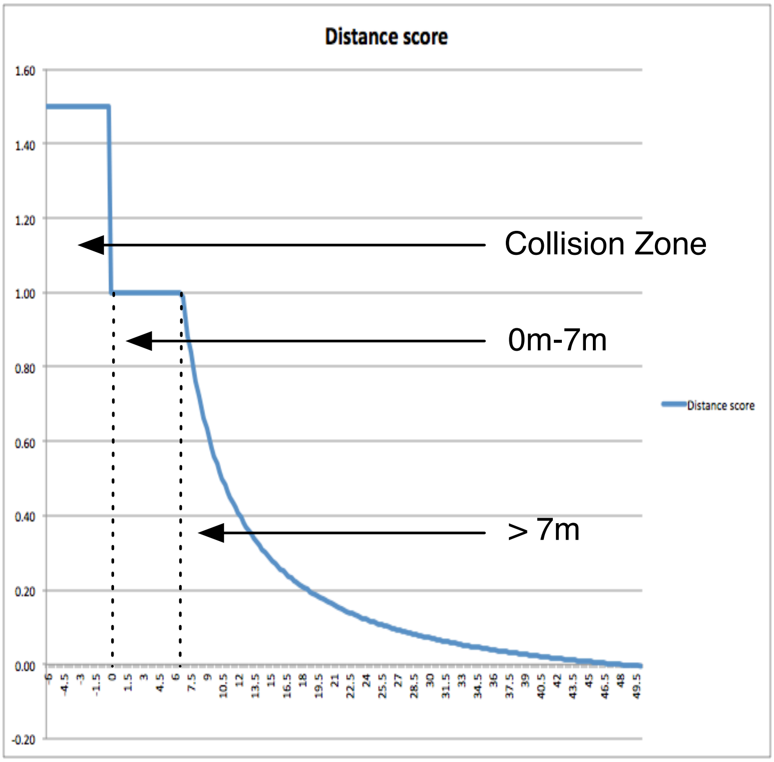


Figure 4.5: This graph shows the variation of distance score with distance (in metres) used in experiments. A score of 1.5 if a collision has already occured, a score of 1 if it is within 7m and an exponentially decreasing score beyond that distance

sensed and the final list of percepts $p*$ is obtained. In case two objects have the same score, the objects that are moving towards the perceiving agent are given precedence, subsequently closer objects are given preference.

This shortened neighbor list is passed to RVO2 [83] for calculating the velocity at each time step. Our hypothesis is that the 3-step perception process presented in this chapter provides an improvement in two ways: Firstly, there are fewer neighbors and hence, fewer constraints for a given sensor range. Secondly and more importantly, more human like results can be obtained as will be illustrated in Sect. 4.4.

4.4 Model Evaluation

This section evaluates the validity of the model. This is done in two ways. First, Section 4.4.1 presents a preliminary visual and quantitative validation of the proposed model. Section 4.4.2 then validates the model against real world experiments.

4.4.1 Model demonstration

The ideas introduced in Sect. 4.3 are used as the basis for visually validating different aspects of the proposed model. For quantitative validation of the model, two measures are used: *Effort Expended* and *Inconvenience Cost*. In proposing their least effort

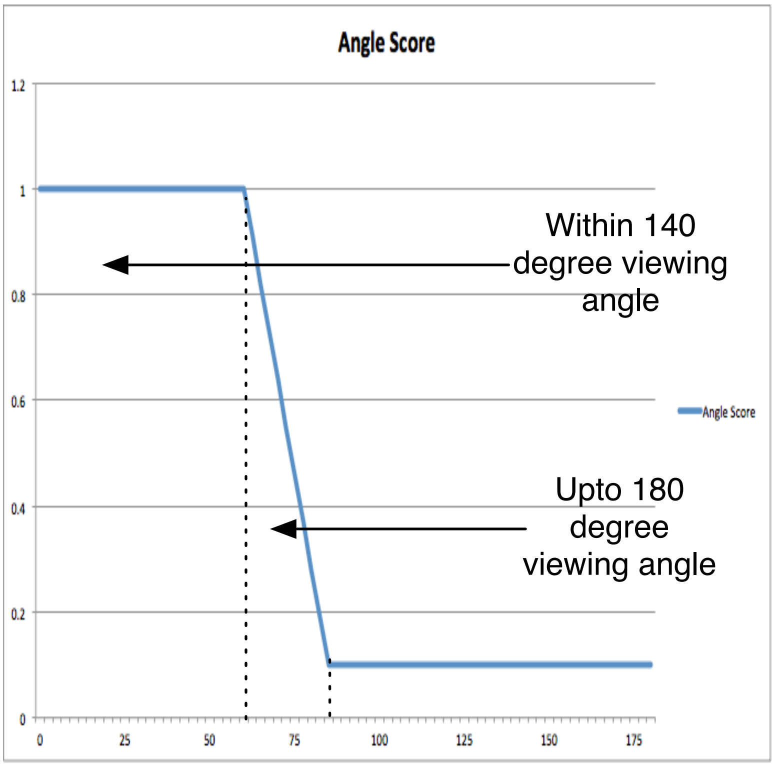


Figure 4.6: This graph shows the variation of angle score with the angle(in radians) formed by the object with the agent used in experiments. For objects forming an angle of less than 70° (viewing angle 140°, a score of 1 is given. For objects forming an angle of up to 90°, the score linearly decreases to 0.1 which is the angle score for all remaining obstacles.

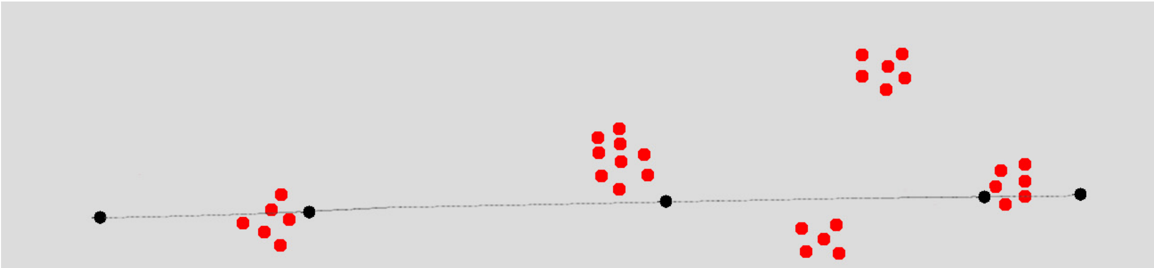
based approach to motion planning [6], Guy et al. used a measure of effort expended to demonstrate the usefulness of their model. This effort was calculated as follows:

$$E = m \int (e_s + e_w |\vec{v}|^2)\, \mathrm{d}t \quad ^3 \tag{4.7}$$

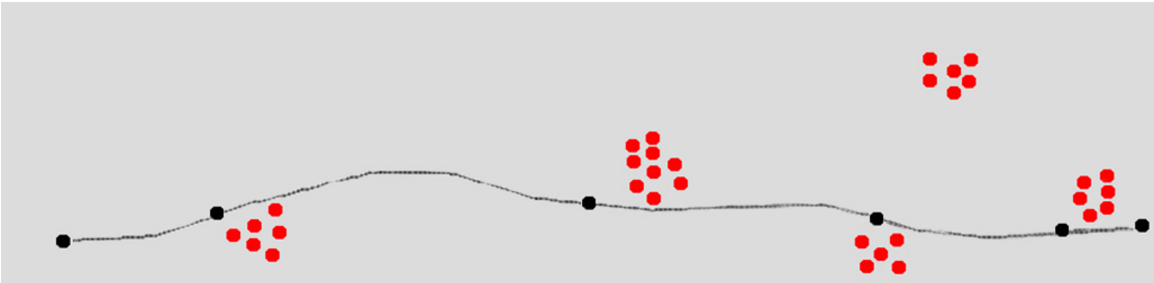
In this section, the same measure of effort is used to analyze and validate the proposed IBP model. For simplicity, all agents are taken to have the same average mass of 70 kg. However, this only measures the mechanical effort involved. To measure the amount of effort spent in decision making, an *inconvenience cost* measurement is introduced. The inconvenience cost is the number of time steps in which the agent chose a velocity other than its preferred velocity i.e., the number of times they had to avoid a collision.

Four different scenarios are considered to evaluate the overall performance. First, the effect that Group Based Perception can have on an agent moving through a crowd is demonstrated and the scenario is visually and quantitatively analyzed. Next, the effect of the multi-layered clustering on an agent moving towards a large group is similarly analyzed. Following this, the necessity of Group Based Perception (GBP) in modeling the information processing limits of human beings is shown.

[3] $e_s = 2.23\frac{J}{Kgs}$ and $e_w = 1.26\frac{Js}{Kgm^2}$ for an average human [100]



(a) Traditional Circular Sensor Range



(b) Group Based Perception

Figure 4.7: Experiment 1: Group Based Perception

Finally, the importance and relevance of the information threshold is demonstrated by demonstrating the effect that it can have on an agent.

4.4.1.1 Group Based Perception

In this experiment the results of using RVO2 with a traditional simple circular sensor range against RVO2 with a Group Based Perception system is shown. The intention is to show the effect of perceiving agents as groups. The hypothesis is that by perceiving groups as obstacles the simulation will generate more visually natural motion. In Fig. 4.7, there is a single black agent moving towards the right, and a number of groups of red agents moving towards the left. The black trail shows the path that is taken by the black agent. It can be seen that in Fig. 4.7a where GBP was not used, the agent walked through other groups. Since RVO2 enforces each agent to do half the work to avoid collision, the agents within the group individually give way through its center for the oncoming agent to pass. At present this argument is based on the discussion in Sect. 4.1, due to social norms and the human tendency to group information together people generally try to move around an entire group rather than walking directly through a group. As shown in Fig 4.7b the GBP algorithm is capable of generating motion which avoids entire groups.

An analysis of the effort expended and the inconvenience cost gives some interesting results. Since the simulation is executed for a given number of time steps, the effort expended is normalized with the progress towards the agent's goal. This is to avoid slow or stationary agents from being considered to be more efficient despite traveling a lesser distance. On comparing the normalized effort in the two scenarios of the black agent, it is found that despite having a much longer path, the

Table 4.1: Quantitative analysis of Group Based Perception

Agent Considered	Effort ($Jm^{-1} * 10^5$)		Inconvenience Cost	
	Without GBP	With GBP	Without GBP	With GBP
Black Agent	71730	71726	120	148
All other agents (average)	1884	1880	14.28	6.56

GBP enabled agent expends slightly lesser (practically the same) amount of effort than the other. This is because the non-GBP agent has to slow down to wait for the other agents to give way before it can proceed and thus progresses less towards the goal.

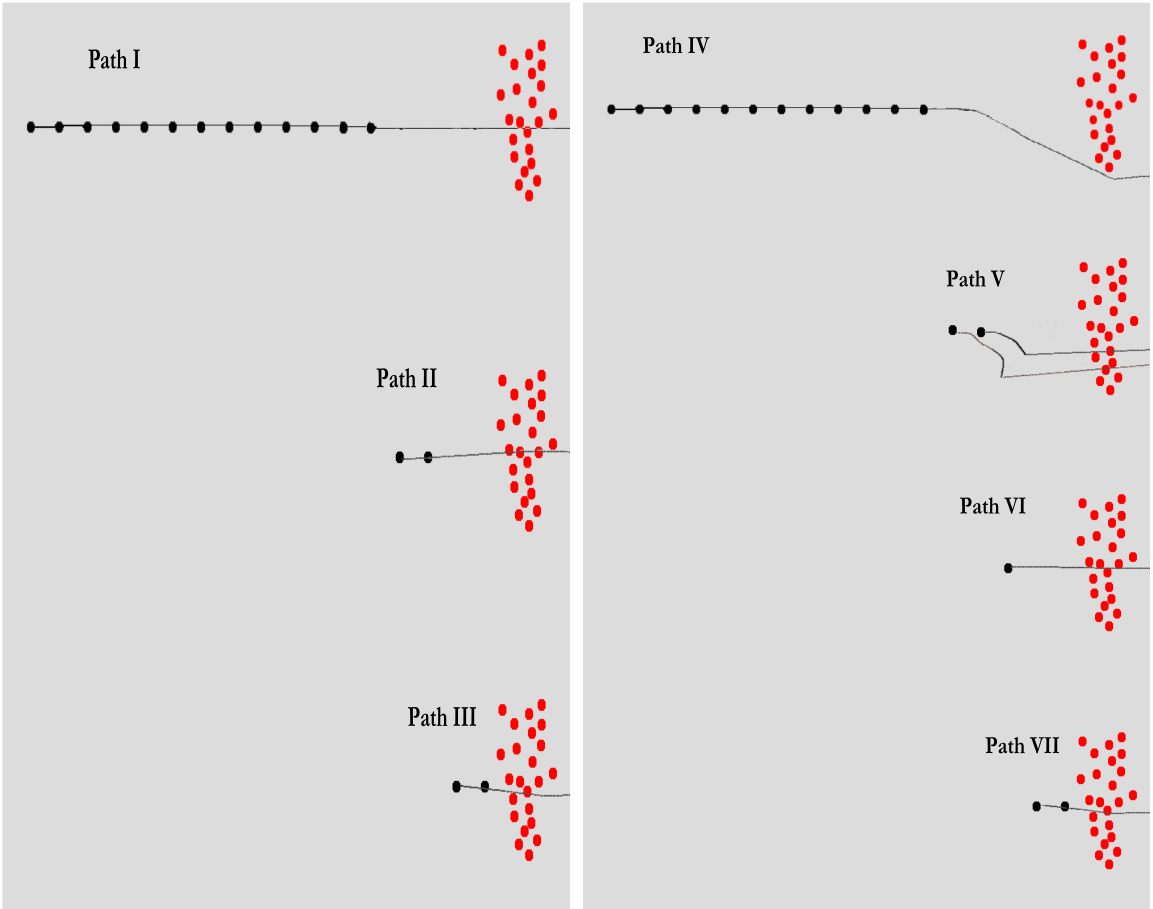
The inconvenience cost comparison gives another interesting, though not surprising, result. The inconvenience cost to the black agent of using Group Based Perception is higher because of the more indirect path that it has to take. However, the average inconvenience caused to all the other agents is significantly lesser. This is consistent with the general human reluctance to inconvenience others. It also gives the interesting idea that even if the same amount of mechanical effort is expended in following two different paths, the amount of decision making required for each path might be significantly different.

4.4.1.2 Effects of multi layered clustering

In this experiment, the simple scenario where a single (black) agent had to get past a big group of agents to get to its goal is studied. The same experiment was performed by keeping the agent at different distances from the group. The objective of this experiment is two-fold. Firstly, it demonstrates the importance and the working of the multi-layered clustering (Sect. 4.3.2) used. Secondly, it demonstrates that when agents are very close to each other, where RVO2 already performs well, the Group Based Perception does not interfere with RVO2's functioning.

To recap, the multiple layers are used to describe groups of varying size at varying ranges of perception. This means agents will perceive other agents as groups or individuals depending on the distance; as an agent moves towards a group it will start to perceive the group as individual agents.

When GBP isn't used, the path followed does not change significantly with distance. The agents in the path of the black agent, give way to the agent, and the black agent just proceeds straight through the center of the large group (Path I in Fig. 4.8a). In the last few cases (Paths II and III), the path is slightly different because the black agent does not have enough time to plan for a smooth, straight path and hence there is a slight deviation. Also, similar to the experiment in Sect. 4.4.1.1 it is forced to slow down in the process.

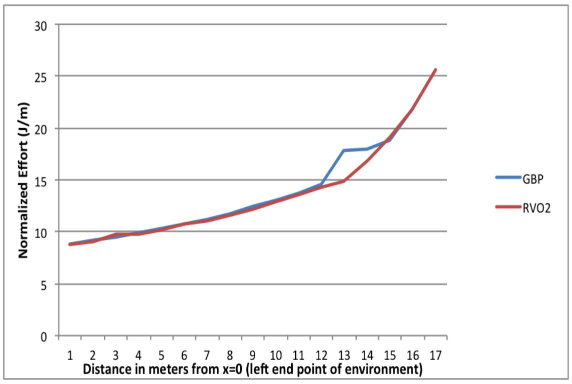


(a) Using traditional sensing (b) Using Group Based Perception

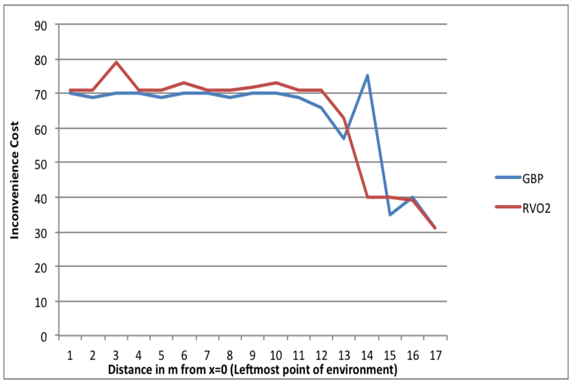
Figure 4.8: Experiment 2: Effect of multi layered clustering

The result produced when GBP is used is more varied. Four distinctly different paths (labeled IV, V, VI and VII in Fig. 4.8b) are produced based on how far the oncoming black agent is from the big group. At distances between 7-18m away from the center of the big cluster, the agent has enough time to perceive the group and avoid it completely (Path IV). At distances between 5-7m away, due to the size of the group, the agent gets too close to the group such that it then perceives the group as individuals. At this time (as described in Fig. 4.4) the agent performs motion planning on all the individual agents and as a consequence moves through the group, shown by path V. Path VI is obtained in a similar fashion; however, the black agent is too close to the group (4m away) to discern the effect of GBP. At distances closer than this (2-3m away), the path followed by the agent (Path VII) is exactly the same as that followed by the agent not using Group Based Perception (Path III). We argue that this type of flexibility in the perception of groups is critical to creating more natural behavior, humans will adapt what they perceive based on success or failure of their attempt to avoid larger groups.

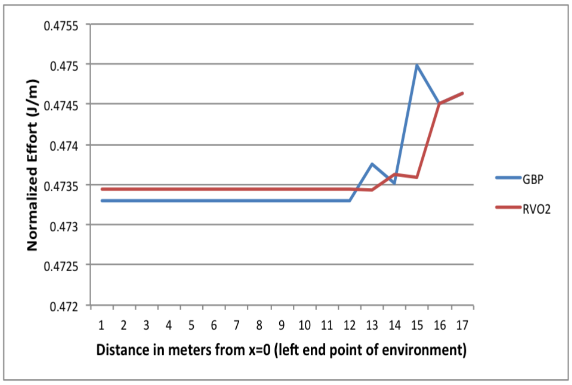
Figures 4.9a and 4.9c show a comparison of the effort expended by the black agent and the average effort expended by all the remaining agents while using a traditional sensor range and GBP. As in the previous experiment (Sect. 4.4.1.1)



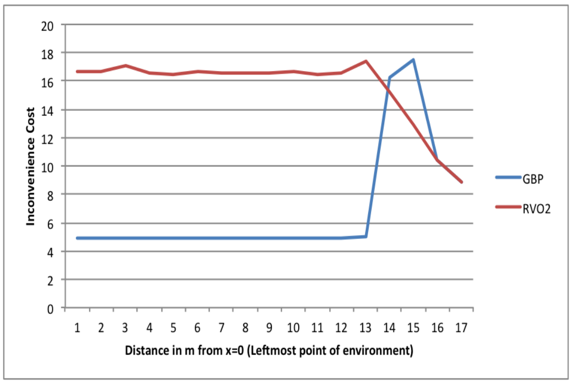
(a) Black Agent- Effort



(b) Black Agent- Inconvenience



(c) Remaining Agents- Effort



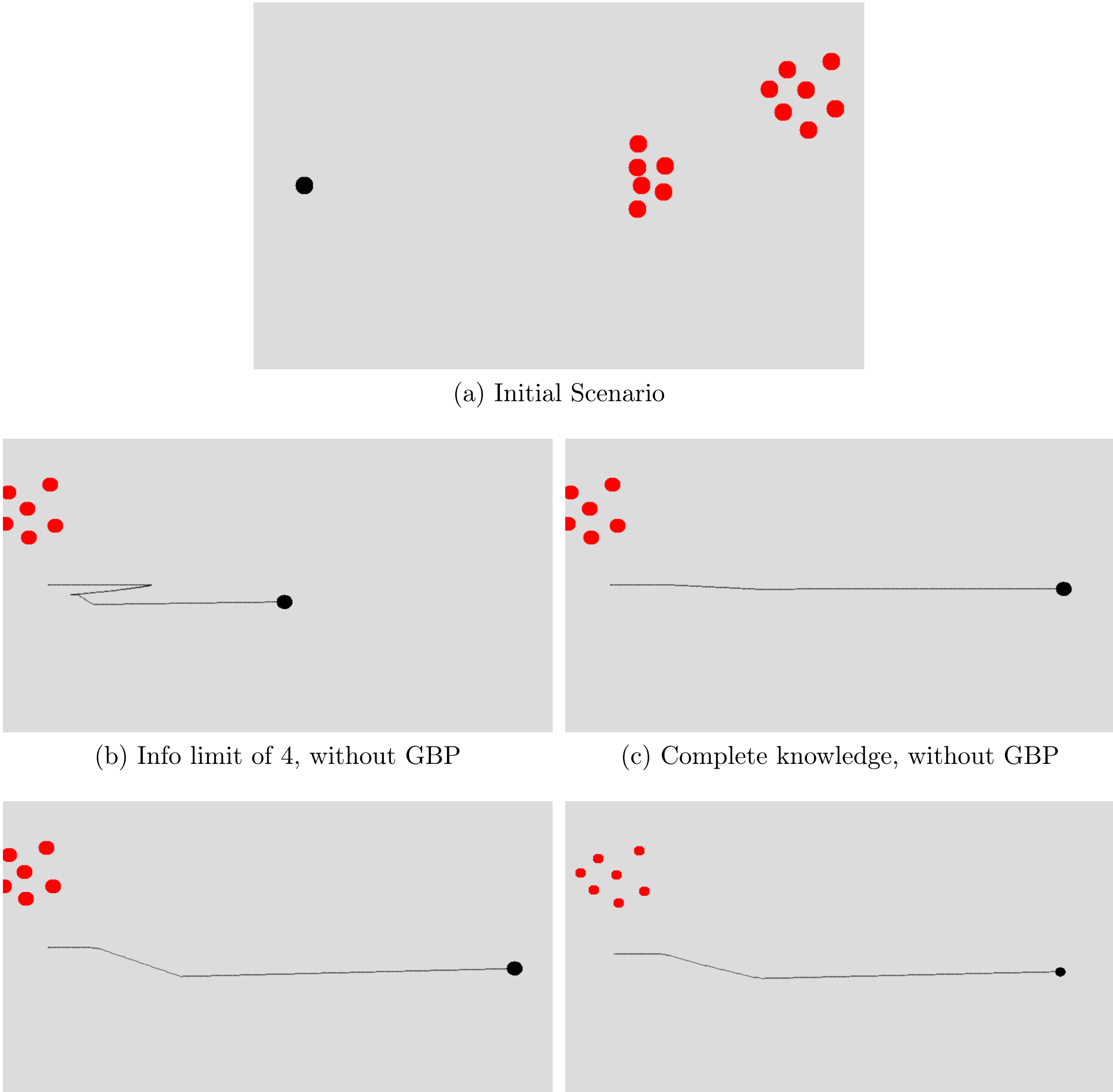
(d) Remaining Agents- Inconvenience

Figure 4.9: Experiment 2: Quantitative Analysis

there is hardly any difference in the effort expended in both scenarios (except for a slight increase for path V). However, an interesting pattern can be observed in the inconvenience measurement (Figures 4.9b and 4.9d). Firstly, the inconvenience for the rest of the group, is always lesser when GBP is used and almost the same for the black agent when path IV is followed. However, when path V or VI is followed there is a spike in the inconvenience curve. This can be explained by considering the fact that in both path V and VI, the black agent changes its planned path suddenly and decides to go through the group, thus not only increasing its own inconvenience but also the inconvenience caused to others in the group who have to move to give way to the agent. Finally, when path VII is followed both the effort and inconvenience count are exactly the same as for path III.

4.4.1.3 Filtering necessitates Group Based Perception

In Section 4.3, the fact that humans have limited information processing capacity was explained. In this experiment, it is demonstrated that if a human being's limited information processing capability is to be modeled, it is necessary to use Group Based Perception. This is done by observing the simple scenario of an agent moving towards two groups of other agents (Fig. 4.10). When no information limit is imposed on the agent, and a normal circular sensor range is used, the agent, as expected, follows a



(a) Initial Scenario

(b) Info limit of 4, without GBP

(c) Complete knowledge, without GBP

(d) Info limit of 1, with GBP

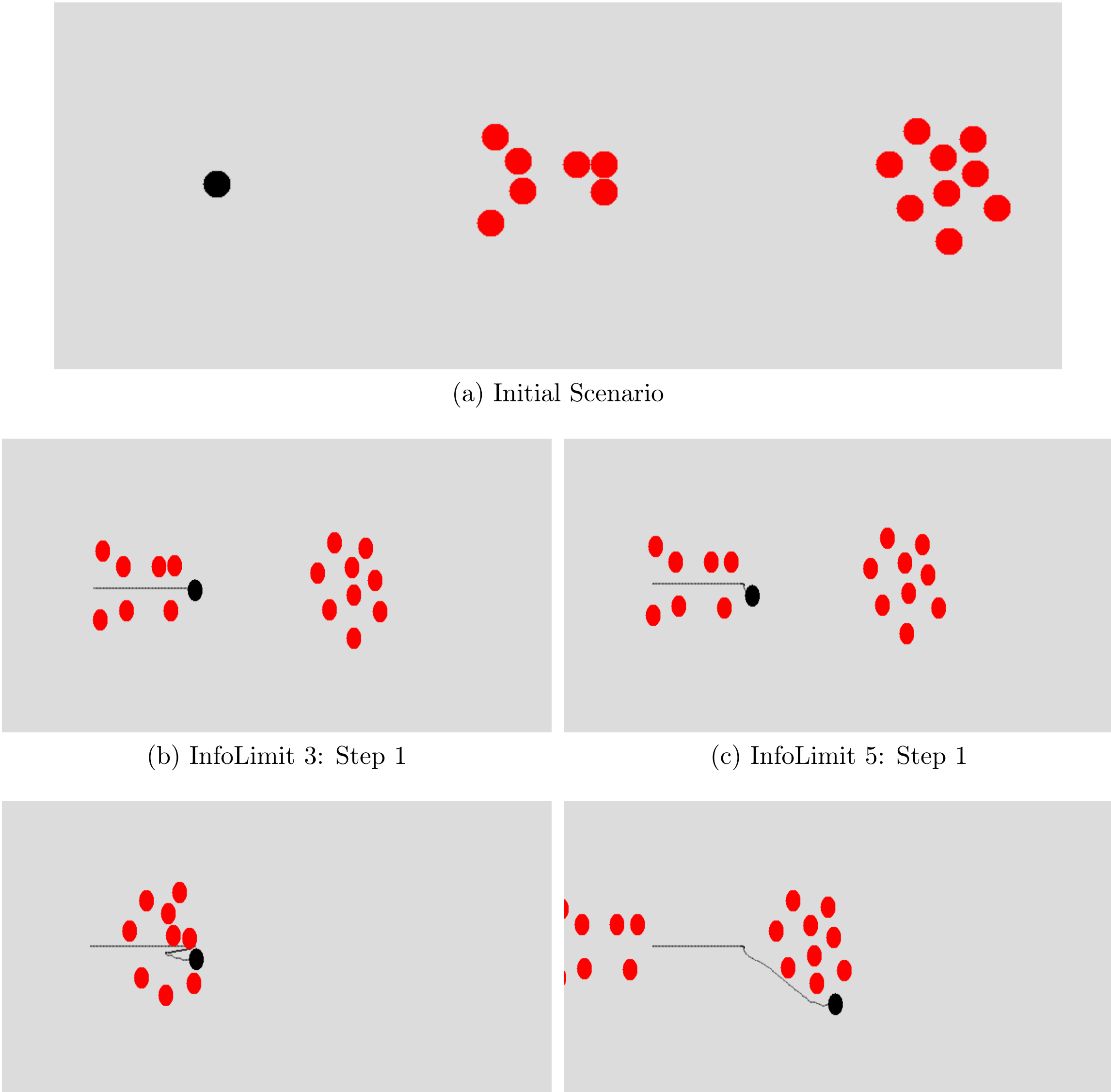
(e) Info limit of 4, with GBP

Figure 4.10: Experiment 3: The necessity of Group Based Perception

nice straight path through the center of the group. However, when an information limit of $a_{IL} = 4$ is imposed on the agent, the black agent, does not perceive all the individual agents in the group and as a result it is forced to reconsider its path mid-route. As a result, the irregular trail shown in Fig. 4.10b is obtained. However, in the same situation, when Group Based Perception is used, the agent smoothly avoids the whole group (Fig. 4.10e). In fact, this smooth path is obtained for as low a limit as $a_{IL} = 1$ (Fig. 4.10d).

4.4.1.4 Effect of filtering of percept information

The final experiment (Fig. 5.2) demonstrates the effect of filtering, i.e. having limits on the information processing capabilities of the agents. The scenario consists of an agent moving towards a collection of individuals (moving towards the agent) followed by a group of agents behind the set of individuals. In the first case an information



(a) Initial Scenario

(b) InfoLimit 3: Step 1

(c) InfoLimit 5: Step 1

(d) InfoLimit 3: Step 2

(e) InfoLimit 5: Step 2

Figure 4.11: Experiment 4: Effect of filtering of percept information

limit of $a_{IL} = 5$ is set so that the agent is continually capable of perceiving a larger number of other agents and groups. In the second scenario a lower limit of $a_{IL} = 3$ is used such that the agent isn't initially capable of perceiving the group behind the individuals. Figure 4.11c shows how agents perceive the cluster that is farther away, even when there is an immediate collision to avoid. Figure 4.11e shows that the agent manages to move around this group because it had a head start in planning - i.e. , it considered the group early when avoiding collisions. In the second scenario it could process a maximum of 3 or 4 percepts at any given time because of the lower information limit. Due to this, as seen in Fig. 4.11b, the agent cannot see beyond the immediate obstacles in front and does not prepare in advance to avoid the larger group. Once the agent finally perceives this group, it is too late to move around this group as it perceives the group as individuals and then moves through the group as in Fig 4.11d.

This experiment illustrates how small differences in the information limit can generate different forms of behavior in the agents. Interestingly, the info limit of 3 and 5 correspond to Cowan's finding [86] that all humans can cognitively process only 3-5 chunks of information at any given time. Clearly the value of the limit is critical to behavior, it is also proposed that this limit will change with personal characteristics and the emotional state of the agents. In fact this varying limit of perception may be an important factor for collisions in actual crowds, this is especially relevant in emergency egress scenarios where stress and collisions are critically important to safety planning. We plan to attempt to quantify this information limit through experimentation in future work.

4.4.2 Experimental validation

Hu et al. [? ?] conducted a series of controlled field experiments to study the interaction among individual participants and their movement in certain scenarios. In this section, the experimental setup used by Hu in his thesis is first reproduced. Following this, the results obtained are presented and compared against the results produced by RVO2 agents using Information Based Perception.

4.4.2.1 Experiment setup

This section explains the experimental setup and measurements made by Hu et al. to study human movement in particular scenarios [4]. In the original paper three experiments were conducted, since IBP does not produce results different from the underlying motion planning algorithm used (RVO2 in this case) for two of the scenarios only the first experiment analysing movement of pedestrians walking towards each other is presented and considered in this analysis.

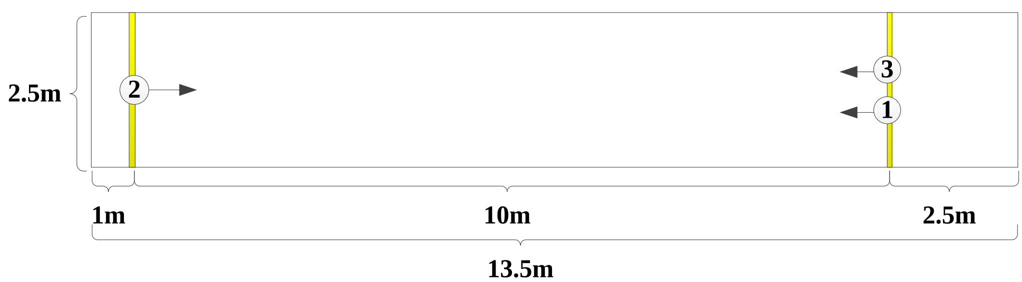


Figure 4.12: A 13.5 m x 2.5 m area is demarcated for the experiments. The participants stand 10m apart and are directed to walk towards the other end at their prefered speed.

[4]This section simply summarizes the experiments conducted by Hu et al. to provide a context for the subsequent analysis and validation done. For a more detailed discussion please refer to the original paper and thesis.

The experiments were conducted at an outdoor passage outside the School of Computer Engineering in Nanyang Technological University. Figure 4.12 shows the setup of the experiment. Each experiment consisted of three participants (marked 1, 2 and 3) moving at their preferred speed in the given direction until they reached the goal point marked by the border of the demarcated area. Hu et al argue that this scenario is typical of several real life bi-directional movement scenarios. In order to shift attention from movement, the participants were given some simple algebraic calculations to do as they move. The experimental setup is shown in Figure 4.13. A video camera with adequate resolution was kept at fixed height above the experimental area using a horizontal tripod. The location of the camera and the lens was fixed to ensure maximum clarity and minimal distortion. Markers were kept on the experimental area to prevent participants from going outside the experimental area and to help in analysis of results obtained. Participants were also asked to wear white helmets so that the analysis from the video was accurate [101].

Videos of 20 experiments with 13 participants (9 male; 4 female) were finally analyzed for characteristic movement patterns and other metrics. The process shown in Figure 4.14 was then used to extract the trajectories of each of the participants in each of the recorded videos. Briefly, the process was as follows: first the video was converted into a series of images at 20 frames per second which is an ideal frame rate to obtain a complete trajectory of the movement of participants. Once an image stack was obtained the image was scaled, rotated and transformed using the markers to remove distortions and bring it to metric scale. Following this the next two steps quantize the image and remove noise such that, at the end of the process, each image only has black and white colors with the former depicting the background and the latter the participants. Lastly, a tool is used for tracking each participant (white particle) in the quantized images. Fig. 4.15 gives an example of the whole process.

4.4.2.2 Quantitative measurements of experimental data

The data extraction process outlined in Section 4.4.2.1 produces for each participant in each experiment a trajectory. Trajectories that were similar were grouped together and normalized to find an average trajectory for each group. It was observed that these trajectories could be grouped into three main groups shown in Figure 4.16. The quantitative measurements that are explained next are all calculated on this average trajectory.

The different measurements used by Hu et al. are very neatly summarized in Figure 4.17. These metrics are:

- Trajectory length of participant i (L_i).
- Maximum deviation of participant i (D_i). This is the maximum value of dd_i^t for a participant over the course of the complete trajectory.

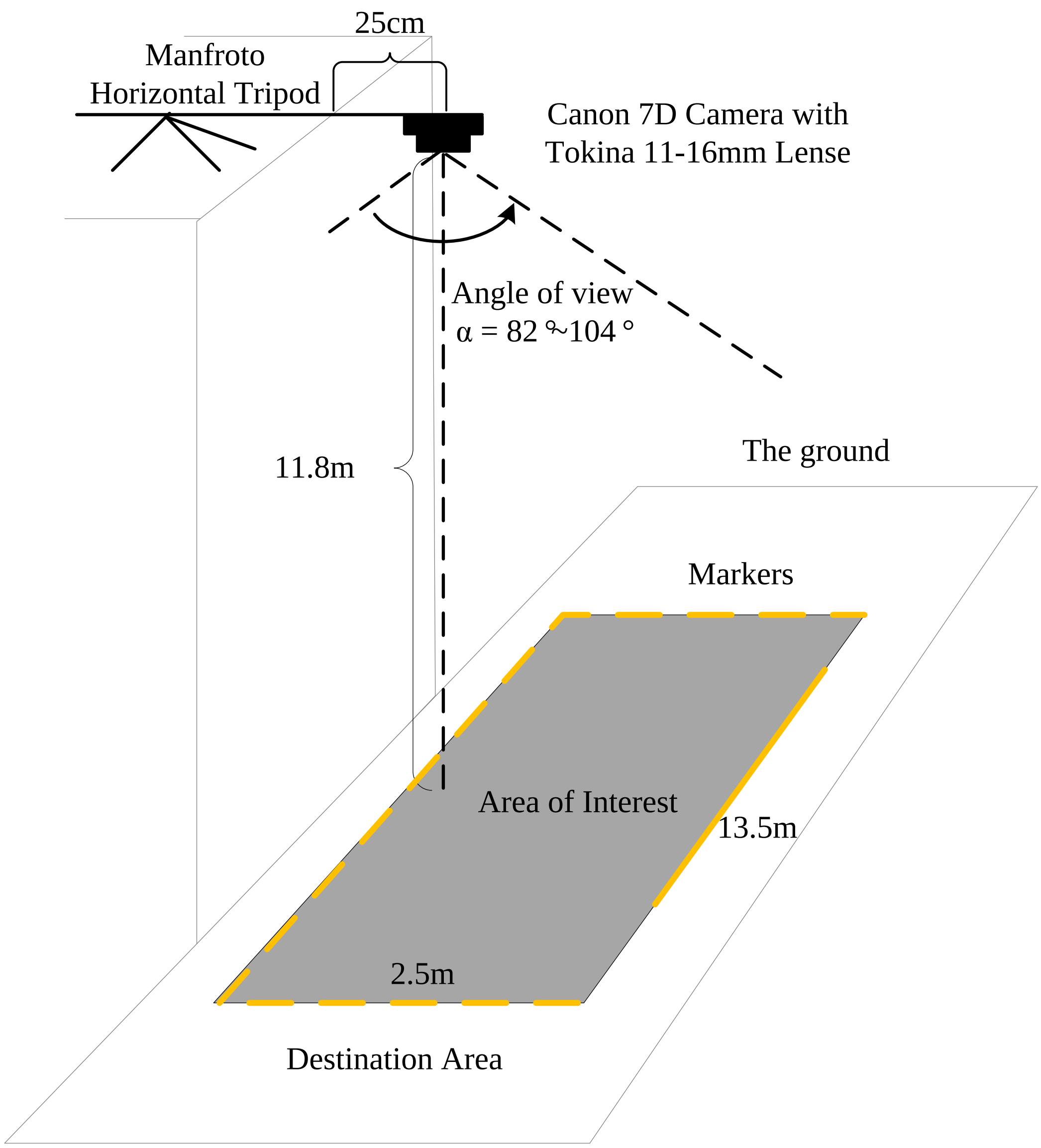


Figure 4.13: The experimental setup used by Hu et al. [?] for their controlled field experiments.

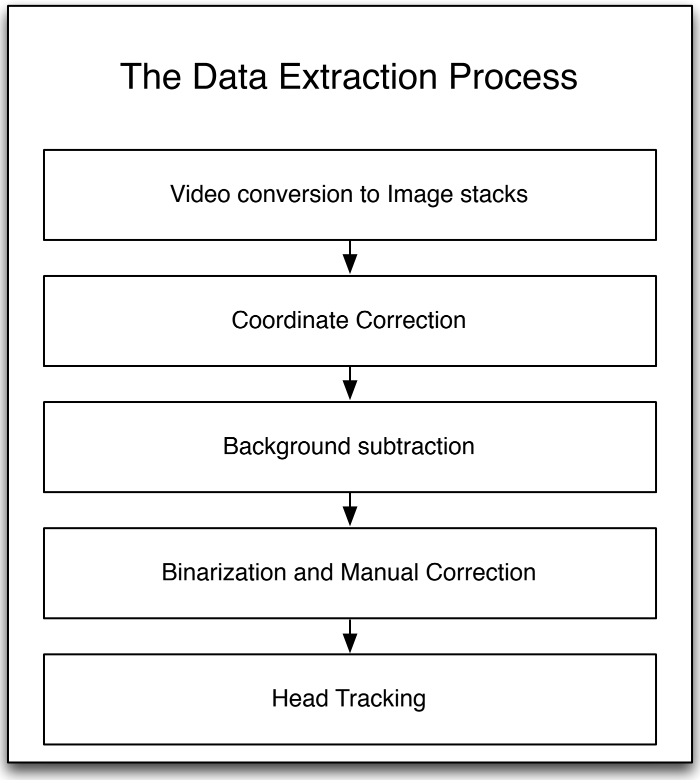


Figure 4.14: The data extraction process.

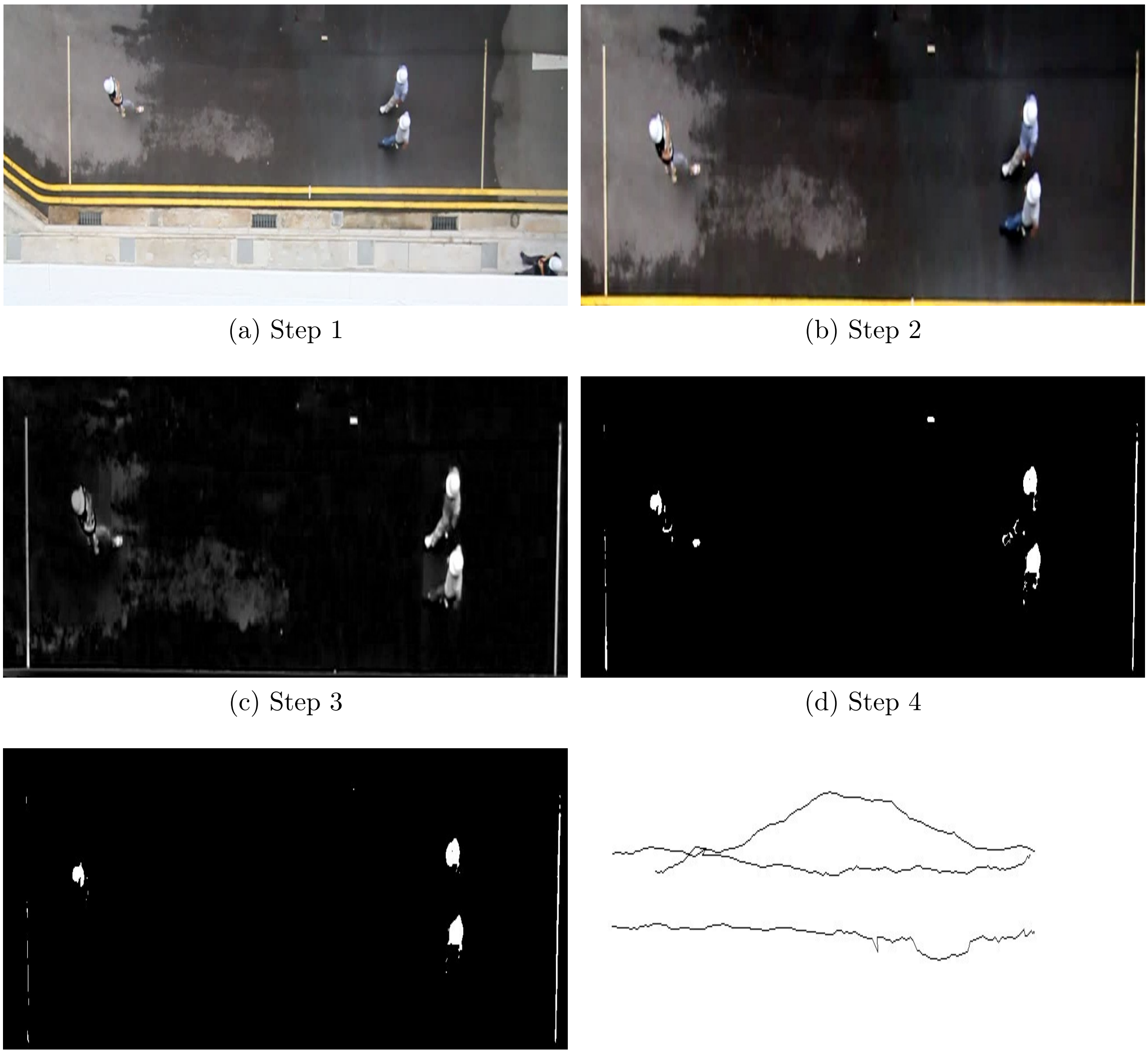
- The speed of the participant as function of time t (s_i^t).
- The distance between agents i and j as a function of time t (d_{ij}^t).

4.4.2.3 Results and comparison

This section presents the simulation results produced using IBP when compared against the experimental data. The experimental setup was replicated by initializing the agents as shown in Fig. 4.18

The metrics in Section 4.4.2.2 can be broadly grouped into two kinds: temporal measures and non-temporal ones. Table 4.4.2.3 shows the non-temporal values for the real world data. It can be broadly seen that in 90% of the cases, Participant 2 avoided Participant 1 and 3 through either side. It can also be seen that the major deviation effort was taken by single agent ($\approx 0.87m$) rather than the group of two agents ($\approx 0.2 - 0.3m$). This also meant that participant 2 on average had to travel a slightly longer distance. Both of these observations can be made of the simulations results produced by RVO2 using Information Based Perception as shown in Table 4.3.

Figures 4.19 and 4.20 illustrate the temporal measurements from the simulation results for RVO2, Social Force and RVO2 with IBP. Hu et al observed that one of the problems with existing motion planning systems was that there was a significant slowing of agent 2 when it gets closer to the other agents (Figure 4.19);



(a) Step 1

(b) Step 2

(c) Step 3

(d) Step 4

(e) Step 5

(f) Step 6

Figure 4.15: An example of the video extraction process

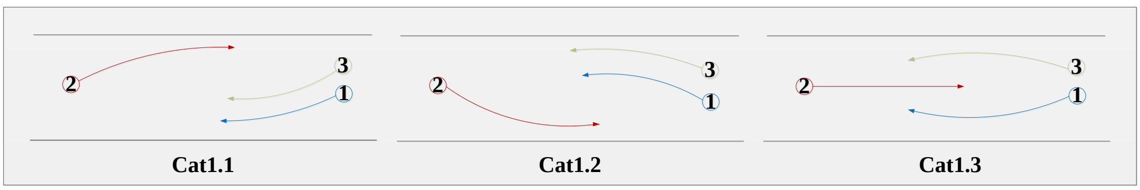


Figure 4.16: The trajectories of participants can be grouped into 3 categories

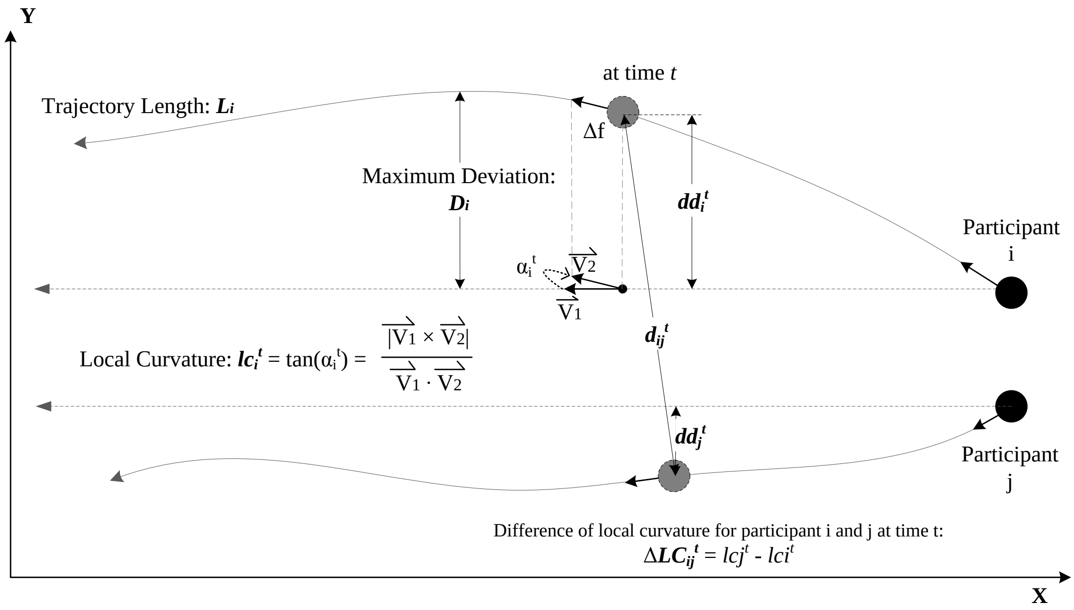


Figure 4.17: Metrics proposed by Hu et al for quantitative validation of models.

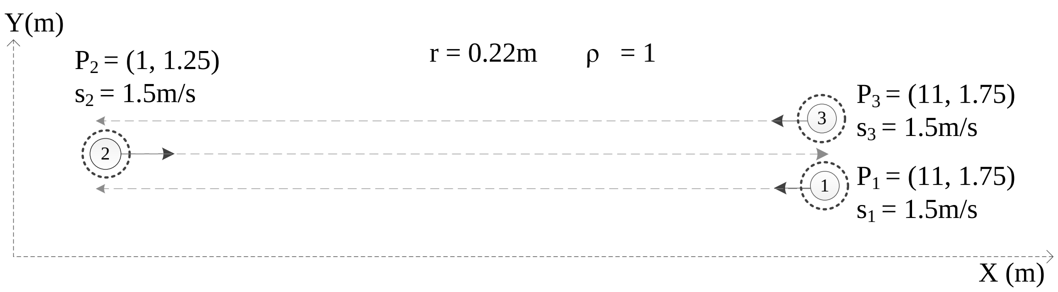


Figure 4.18: The initial configuration of the simulation based on the experimental setup in real world experiments

		Category 1 (**55%**)	Category 2 (40%)	Category 3 (5%)
Maximum Deviation	D1	0.0785	0.320723	0.241166
	D2	**0.8720**	**0.868398**	0.320865
	D3	0.2656	0.18667	**0.657496**
Trajectory Length	L1	10.0542	10.12006	10.15071
	L2	**10.238**	**10.27922**	10.15928
	L3	10.1126	10.0789	**10.18924**

Table 4.2: Maximum deviation and path length according to experiments conducted Hu [**?**]. Category 1 refers to the movement of Agent 2 to the left of the group, category 2 to the movement of Agent 2 to the right of the group and category 3 to the movement of agent 2 through the middle of the oncoming group.

Maximum Deviation	D1	0
	D2	**0.959**
	D3	0
Trajectory Length	L1	9.925
	L2	**12.188**
	L3	9.925

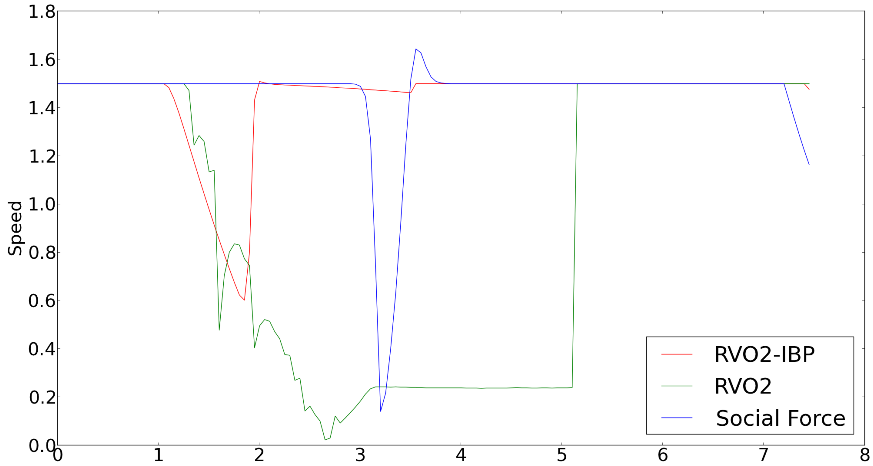
Table 4.3: Maximum deviation and trajectory length obtained for the simulation of the experimental scenario in [**?**]

whereas in the real world results all three participants maintained their speed. When RVO2 is used with IBP there is dip in speed of participant 2 but this lasts for less than a second as shown in Fig 4.19. For the rest of the simulation, the agent maintains it's speed.

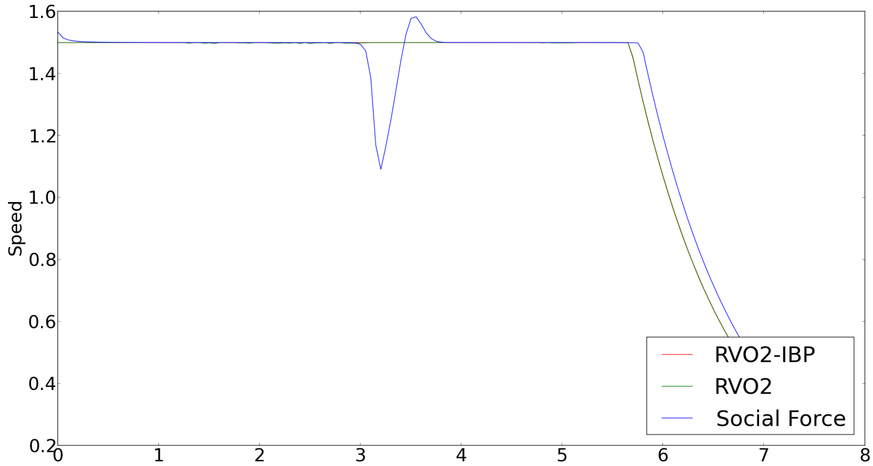
Fig. 4.20 shows the inter agent distances as a function of time. As in the real world experiments of Hu et al. it can be seen that agents 1 and 3 maintain a relatively constant value. It can also be seen that, at it's closest point, as in the experiment, agent 2 becomes closer to one of agent 1 and 3 than they are to each other. This is better than the results produced by RVO2 and Social Force using a normal sensor range as shown in Fig. 4.20c and Fig. 4.20d.

4.5 Summary and Future Work

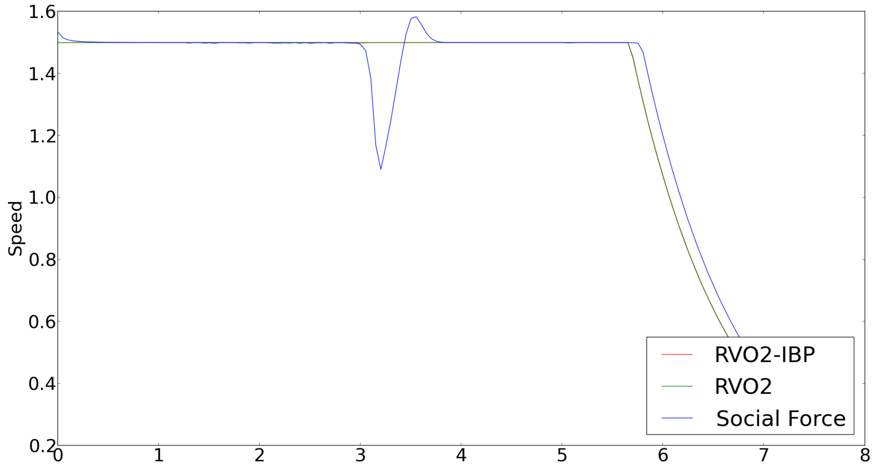
In this chapter, an Information Based Perception model for agents which is based on perceived information rather than spatial distance has been introduced. It's been argued through that this is a more appropriate model of human perception for crowd and egress simulation. The behavior of this system has been demonstrated through experiments and compared to the results produced by real world experiments. It has been shown and argued that this creates more realistic group avoidance behavior. The idea that humans have limited perception capacity such that they only process certain obstacles more relevant to collision avoidance is incorporated; this in turn will result in a reduction in efficiency of collision avoidance. The real world experi-



(a) Agent 2



(b) Agent 1



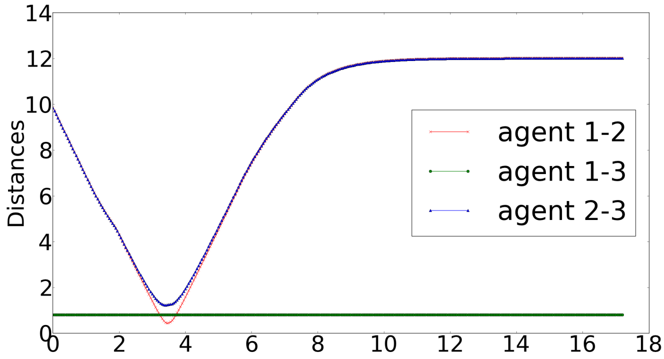
(c) Agent 3

Figure 4.19: Plot of speed against time for various models and the experimental data.

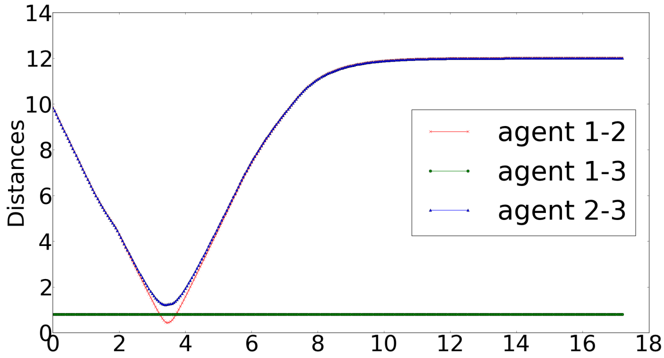
ments conducted by Hu et al. were introduced and comparison of simulation results against experimental results showed that Information Based Perception can replicate the results produced by the experiments.

The IBP model can be extended so that during filtering it can recognize cues that contain event and environment information as well. This can be passed as input to the Event Identification system which is described in more detailed in Chapter 5. Also, one aspect of the model that has not been explored much is the quantification of information limits and appropriate definitions of interest; real world experiments could be conducted to attempt to quantify these parameters. The third criteria which was mentioned in Sect. 4.3.3, i.e. the inherent interestingness of perceived objects, could also be the subject of these real world experiments.

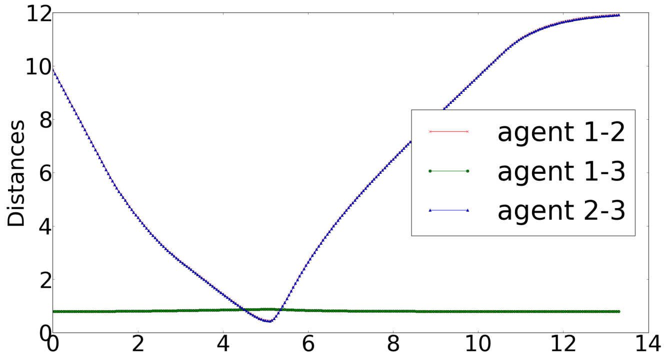
In emergency situations, according to Ozel [17], humans start perceiving cues in the environment differently. The idea of modeling different cues and their effect on the agent's information processing capabilities as suggested by Kuligowski [21] is an idea that will be discussed in more detail in Chapter 5. As mentioned by Hill [91] there is also a reciprocal effect of cognition on perception where agents would turn towards objects of more interest. These could also be incorporated into a later version of the IBP model. In the next chapter, a model for how perceived cues can be used for identifying events and modelling pre evacuation behavior is presented.



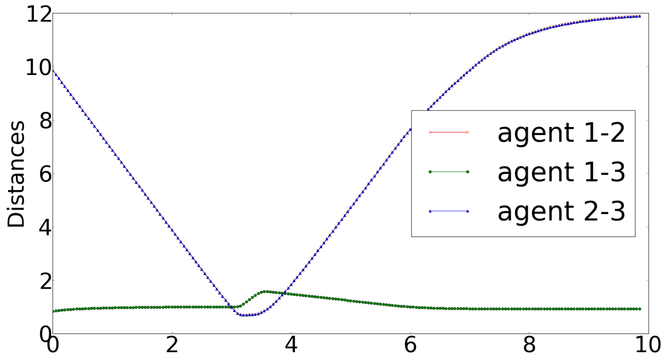
(a) Experiment



(b) IBP-RVO2



(c) RVO2



(d) Social Force

Figure 4.20: Plot of inter agent distances over time for various models and the experimental data.

Chapter 5

Modelling Pre Evacuation Behavior in Agent Based Simulations Of Crowds

[1]

5.1 Introduction

Ideally, when a fire starts a fire alarm goes off; all occupants hear this alarm and use the nearest safe exit to leave the building. However, this is hardly the norm. In many cases, occupants are desensitized from hearing false alarms and often do not start to evacuate until they are completely sure that it is needed. On January 19, 2000, a fire in Boland Hall in Seton Hall University killed three students because they had ignored the fire alarms assuming they were false [34]. This uncertainty about the authenticity of the first sign of danger isn't an isolated incident [32, 33, 37]. Hence, when studying the behavior of evacuees, it is necessary to study and understand their actions from the time at which the fire started right up until the point where the last person evacuated [33].

As discussed in Chapters 2 and 3, pre-evacuation uncertainty and investigation are features of human behavior during egress that are rarely considered in existing models. To recap, *pre-evacuation* refers to the period of time that elapses after the start of the fire alarm before the person starts evacuating. While some models [77] do have a simplified model of pre-evacuation behavior, they fail to model it in enough detail to enable their extension to more general cases. For example, a fire alarm could have different effects based on the clarity and believability of the alarm [12, 15]. This variability is hard to simulate in existing models of pre-evacuation behavior. Also, during an evacuation people exchange event and environment related information with others. Evacuees are unlikely to follow blindly any and all messages

[1] This chapter presents a method for modelling pre-evacuation behavior in emergency egress simulation. The model was presented as a poster and short paper at the Pedestrian and Evacuation Dynamics Conference in 2012 [**?**].

that they receive. There is a variability in the *trust* in messages received that can have different effects on egress. This is rarely considered in existing models.

In this chapter, we present a model for simulating pre-evacuation behavior and event identification in agent based simulations of crowds [2]. In the model, the evacuees identify and process information in terms of event cues which exist throughout the environment. Section 5.4 illustrates the importance of modeling pre-evacuation behavior and a communication system is illustrated through experimentation.

5.2 Related Work

A fire evacuation is a complex situation to model and simulate. A large component of this complexity is the need to model the behavior and decision making of the people taking part in it. As discussed in Section 2.2, there are a lot of conflicting theories on how humans behave in emergencies and why they behave as they do. However, there are also certain parts of human nature that are generally accepted to be true, such as the constant search for information [16, 17, 32, 33]. This section first summarizes the existing knowledge of human behavior during egress with special emphasis on pre-evacuation behavior. Following this, some existing models of pre-evacuation behavior and communication is presented.

5.2.1 Pre-evacuation behavior

Several studies of human behavior during emergency egress [17, 38, 55], have shown that an evacuee's first reaction after realizing that there is an unusual situation is to investigate and gather more information about the situation. Evacuation starts only once the need for evacuation is established. *Cues* are the key to understanding this transition from realization to investigation and, eventually, to evacuation. Cues are certain changes in the environment that indicate that something is wrong or different from normal [16]. They come in a variety of different forms. Fire and smoke are the typical and most unambiguous cues for an evacuation. Fire alarms and people running about are examples of more ambiguous cues. According to Proulx [38], an ambiguous cue by itself does not cause a person to initiate investigation. Rather, the cue has to persist for a period of time before investigation begins.

There have been several surveys, interviews and other studies of the factors that influence evacuation and pre-evacuation behavior. Kuligowski [21] summarized the key findings of these studies and compiled a list of factors that influence pre-evacuation behavior (Table 2.1). She suggested that the period that we term as pre-evacuation itself consists of two phases. Phase 1 is called *perception*; this refers to the perception of some unusualness in the current situation. Kuligowski calls the next

[2] This

phase *interpretation*; during this phase, the person searches for more information to verify whether a fire has actually started and if it actually poses a threat that needs to be handled. Several others [17, 33, 38] have also emphasised the importance of this phase though sometimes under different names. Regardless of what it is called, this phase consists of two parts: 1. defining the situation as a fire and 2. defining the risk that the situation poses.

Kuligowski categorized the factors that influence these phases into two types: occupant based factors and cue based factors. Occupant based factors are intrinsic characteristics of the evacuee like age, experience, gender, etc. One of the factors that encourage the programmatic implementation of cue based factors is the fact that the effect of a cue can be explained to be caused by the nature and characteristics of the cue rather than the specific cue. In other words, each cue can be described in terms of its ambiguity, consistency with other cues and its source and it is this description that determines the effect of the cue.

5.2.2 Existing models

As mentioned in Section 5.1, there are very few existing models that take the pre-evacuation period into consideration. Pires [18] modeled the pre-evacuation decision making of an individual using a simple Bayesian Belief Network (BBN). França et al. [27] created a simulation model of the development of panic behavior during emergency egress. This model implemented the hysterical belief theory [9] and modeled how panic first develops and then evacuation happens. It also had a basic communication system through which agents exchanged mood information (which is a key factor in the development of panic) by using the grid based environment as a medium for communicating messages. Despite pre-evacuation behavior being modeled in some detail, it is not possible to extend this model to replicate the heterogeneity in people's reaction to cues. ESCAPES [77] is a fairly recent model that takes into account some factors like the spread of knowledge, fear and emotion between the different evacuees. These factors are used to create a simplistic model of pre-evacuation behavior. The event identification and communication model proposed in this paper have been influenced by these models but is unique in the way that the diversity of cues and their effects can be considered.

For the purpose of this paper, three kinds of behavior are modeled: normal behavior where the goal is the center of the *home* room of the agent; *milling* behavior where the agent gathers with other agents at the nearest *corridor* (See Figure 5.1); and *evacuation* where the agent heads towards the nearest exit.

Communication between agents is also modelled with agents being able to transmit messages within a fixed communication range. The working of this communication is explained in more detail in Section 5.3.

To recap the discussion in Chapter 3, the planning system of the agent on identifying a goal passes this goal to the Navigation System that proceeds through a three-level process to determine the preferred velocity of the agent. At the highest level, a logical path is determined in terms of rooms to be crossed from the agents current location to the goal. From this logical path, spatial way points or locations are extracted by the next level. The third and final level determines a possible collision free path to the farthest visible spatial waypoint. In the experiments in this chapter, A-Star is used for path planning and RVO2 is used for the motion planning system.

5.3 Event Identification and Pre-evacuation Behavior

It is known that the ambiguity, source and consistency of the cue [16, 33, 55] are the key factors (Section **??**) in determining the effect of a cue. In the IBEVAC model, this is used in modeling all cues in the same way. Each object or event that is to be perceived as a cue implements a *Cue interface* which ensures that each cue can be explained in terms of its ambiguity, source and consistency. This is one of the key novelties of IBEVAC's approach to behavior modeling. Each cue is located at a particular location in the environment and is sensed by agents when within their perception range.

Once perceived, these cues are passed to the Event Knowledge Module. The module has a *bucket* of information corresponding to *uncertainty* and another corresponding to *fire*. When a cue is perceived, appropriate amount of information is added to the appropriate bucket(s) based on the ambiguity level. A less ambiguous cue contributes more information. For each bucket, a *threshold* is initially fixed by the ADM. When the amount of information in a bucket overflows the threshold, a trigger is sent to the Planning Module to change the agent's state and strategy.

Communication is implemented as *messages* sent from one agent to the other. Each message has a message cue and environment information. The message cue works just as other cues. Here the term ambiguity is used to refer to the trustworthiness of the source of the information. In this paper, the environment information that is passed is only about the inaccessible paths in the map. During an IBEVAC simulation, a cellular automata based fire model and a simple finite difference smoke model are executed. This creates fire and smoke cues at locations near the fire. As soon as the fire starts, fire alarm cues are placed all over the environment. Agents react to these cues and mark observable pathways that are blocked as inaccessible in their Environment Knowledge Module. All agents either escape or are killed at the end of the simulation.

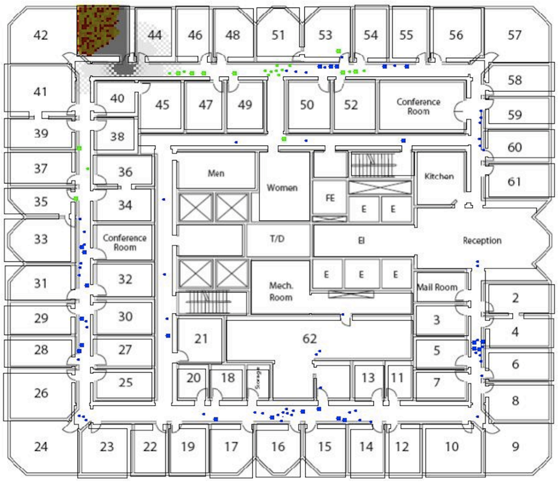


Figure 5.1: First of two floors from World Trade Center, California. Fire is started in the corner room and generates smoke. Fire kills agents. Smoke depending on concentrations slow or kill agents. The longer rectangles are corridors connecting rooms and the open area on the right center is the exit.

5.4 Results

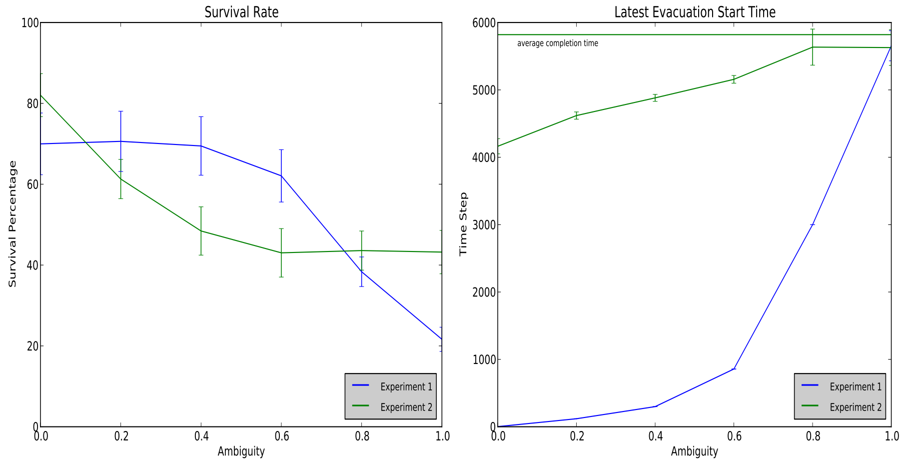
Experiments were conducted using IBEVAC to demonstrate the effect that cue perception and communication can have on egress. Both experiments were conducted on the two floor office environment shown in Figure 5.1. Simulations were conducted with 200 agents randomly distributed all over the environment and data was collected after averaging over 100 replications of the simulation.

5.4.1 Experiment 1: the effect of fire alarm clarity

In this experiment, the effect that fire alarm cue clarity and ambiguity has on egress was examined. It is assumed that the fire alarm can be heard clearly at every location on the map; so cues are placed in every room. A fire alarm with a simple ringing sound is much less clear and more ambiguous than a public announcement system that explicitly states that it is not a drill and gives real time updates about the situation. To examine the effect of this difference in clarity, the experiment was repeated for different values of ambiguity (from 0.0 - 1.0). The blue curves in Figure 5.2a show the error plot of the survival percentage and the one in Figure 5.2b the average time taken for last agent to start evacuating for this experiment. As expected there is a significant drop in number of survivors as the ambiguity of the alarm increases. Also, the later an agent starts evacuating, the lesser is his chance for survival.

5.4.2 Experiment 2: the importance of communication

In this experiment, the effect of message trustworthiness (ambiguity) is modeled. The fire alarm ambiguity is kept at 1.0 to minimize its interference with the effect of message cues. Similar to experiment 1 the cue ambiguity is varied from 0.0 to 1.0.



(a) Average Survival Rate (b) Last Agent Start Time

Figure 5.2: Observations from 100 replications of each setting of the IBEVAC Simulation

The green curves in Figure 5.2a and Figure 5.2b show the results for this experiment. However, both these data are collected for agents in the lower floor only. This is because none of the agents on the higher floor start evacuating as they neither observe the fire nor get a message from other agents about the fire. A similar trend can be observed where the survival rate decreases with increasing ambiguity. The green curve in Figure 5.2b flattens out towards the end because in both these cases, the agent's trust in other agents is so less that the only reason they start evacuating is because of the smoke or fire itself. Another thing to note is that even if all agents are completely trusted (ambiguity=0), the last agent still takes a long time to start evacuating because it takes a long time for the information to propagate to it. This can also explain why there is such a dramatic change in the effect of slight change in ambiguity of the fire alarm cue as opposed to a change in ambiguity of the message cue.

5.5 Conclusion and Future Work

In this paper, the IBEVAC agent architecture for agent based simulation of emergency egress was introduced. A novel cue modeling and perception system which enables the detailed modeling of pre-evacuation behavior has been described and its working demonstrated.

Only preliminary experiments and results were presented in this paper. Further experiments are being conducted in examining the effect of partial knowledge, variability in trustworthiness and other factors. An interesting extension to the cue perception system would be the implementation of a cue memory. This can be used to model agents forgetting about certain cues or being desensitized to cues due to overexposure.

Chapter 6

Modelling Spatial Knowledge

6.1 Introduction

How humans gain and store knowledge of their surroundings has been an area of research for several decades now. A significant amount of research has been conducted in trying to understand how way-finding is done using this knowledge. However, how people explore an unfamiliar environment and the interaction between exploration and memory during this process is still an open question. With the increasing number of shopping malls, airports, high rise office buildings and residential towers, there is an increasing likelihood that the occupants of a building may not be regular visitors and as a result will have very little knowledge of the layout. In such a situation, if there is a need to evacuate the building, it is important for planners to know how the occupants would react and find their way to the emergency exits.

Understanding how people navigate and explore unknown spaces is scientifically challenging. One of the primary reasons is that experimentally studying such processes is difficult and time consuming. Even once an experiment is designed it is always difficult to scale the experiments to many participants and therefore account for various forms of bias due to sampling issues. In recent years serious games (or gamification) have been used in various forms [102–104] to provide controlled, yet realistic environments on which to conduct medium to large-scale experiments of human crowd behaviour. We adopt this same methodology in this paper to gain an understanding of how humans with no knowledge of an environment explore. We do this by developing a novel way of identifying the role that memory and *non-randomness* plays in human exploration. This method involves experiments where participants play an exploration game, in which they are asked to explore a multi-storey building and complete certain tasks within a certain time limit. All the movement and actions of the players were logged and analyzed for patterns. The main motivations of this analysis were to determine:

1. Whether memory plays a role in exploration.

2. How memory influences exploration efficiency and an individuals ability to navigate within an environment.

3. If there are common strategies used by humans to explore unknown environments.

The remainder of this paper is organised as follows: Section 6.2 provides an overview of our current cunderstanding of how people gain spatial knowledge and do indoor wayfinding. Following this, the game and experiment are described in Section 6.3 and Section 6.4. Finally, the results are discussed in more detail in Section 6.5.

6.2 Literature Review

Human exploration of indoor environments is a complex process that depends on the perception of the environment, the person's existing knowledge and cultural factors. Before looking at existing models of human exploration it is useful to establish a basic knowledge of how spatial knowledge is stored, used and updated in the human memory. In the context of this paper, it is also useful to understand the methodology used in studying human spatial memory as both an inspiration and validation for the methodology used here.

6.2.1 Working Memory

Since Hebb's seminal work on human memory [105], it's been generally accepted that human memory has a Short Term Memory (STM) component and a Long Term Memory (LTM) component. Baddeley's model of working memory [106], which is a three component model consisting of the central executive, a visual spatial sketchpad and a phonological loop is currently one of the most popular models of the working of human memory. Central to this idea is the concept of working memory. Working memory consists of both a visual and a verbal component both of which are limited in capacity.

Linberg and Garling [107] presented people with tasks to compltete while at the same time performing way finding. Their findings supported the notion that navigation may require effective use of a limited capacity cognitive sub-systems. Several studies [108, 109] involved experiments examining the way in which way-finding memory was stored. They discovered that when maps were used for learning, only the visuo-spatial component of memory was used. However, in the real world, they found that all the senses were used together and verbal, visuo-spatial, temporal, auditory and even olfactory cues were used by the participants. This suggests that experiments studying way-finding should be as immersive as possible to reflect reality.

Evidence suggests that salient (distinctive) cues are important for place learning. Especially as people grow older and can only perceive and process fewer cues [46] or if the wayfinders are under stress or time pressure [17]. This is because stress and old age can reduce the working memory capacity. A decreased working memory capacity implies a smaller amount of environmental information is processed and less information is eventually encoded. This in turn implies that only cues that have high perceptual, cognitive or contextual salience are perceived [46].

6.2.2 The building blocks of spatial knowledge

There are different scales at which locations are stored in the human mind. This can broadly be divided into 3 levels: Figural Spaces (Object Sized Space), Room Sized Space (Vista Sized Space), Environment Space (Map Sized Space). The approaches used to study these different scales are different [110]. In this research, we only consider Vista and Map sized spaces.

One of the earliest and most influential works on how humans gain and store knowledge of space was Lynch's *The Image of the City* [111]. He coined the term *mental map* which refers to a person's perception of the world around him. Perhaps the most important contribution of this paper was the proposal of the fundamental building blocks of a mental map: paths, edges, districts, nodes and landmarks. Paths are routes along which people move, districts are distinct regions, edges define the boundaries between these regions, nodes and landmarks are locations that are points of reference in the mental maps.

How these blocks form a person's image of space was further explored by Siegel and White [112] through their experiments on map learning in children. They proposed a hierarchical model with three distinct parts. They found out that people first gain a knowledge of the *landmarks* in an area, subsequently they learn *routes* connecting these landmarks and finally they gain *survey knowledge*, wherein they have an overall map of the region to the extent that they can determine shortcuts and best routes. They further postulated that adults, despite not having the limitations of a child, mirror a similar process in forming their memory of space.

Ishikawa and Montello [113] emphasized that different people have different abilities and techniques for formation of spatial knowledge. Significantly, they found out that given repeated exposure to the environment, some people were inherently good and other inherently bad at forming and using spatial knowledge.

Contrary to Siegel and White, they and others [114] also argue that people's route knowledge and knowledge of space does not improve much after first being formed. More interestingly they found out that certain routes are learned and these routes do not change much, however, inter route connections improve as experience increases.

In summary, while people do have different techniques of forming and storing spatial knowledge, most studies have confirmed that there is a definite pattern in which it is formed with landmarks and routes playing a key role at the beginning. Furthermore, studies have also shown that this initial knowledge of routes does not change much with time. This indicates that how people first explore an environment probably plays a key role in determining the route they learn and use even in the longer term. Thus motivating the need to understand better the way in which humans explore environments

6.2.3 Indoor Way-finding

Kuipers [115] believed that people walk in the general direction of their destination and rarely get lost. However, this is not possible in indoor environments where dead ends are much more common [116]. In fact, there are several such differences between indoor and outdoor environments. However, literature on human behavior in internal environments in general, is much more limited. Best [117] was the earliest to identify that the number of choice points, i.e. locations where directional changes occurred, was the relevant measure for assessing way finding difficulty, as apposed to to simple metric distances.

Weissman [118] defined visual access, degree of architectural differentiation, signs and floor plan configurations as the factors that determine way-finding difficulty. *Visual Access* which, in essence, refers to the fact that an environment's external structure gives clues to the internal layout and hence visual access to the outside can decrease way-finding difficulty.

Garling et al. [119] confirmed the findings about familiarity and visual access. Evans et al. [120] discovered that distinct wall colors reduced wall finding complexity. Thorndyke [121] found out that experience does improve way-finding but over the period of months rather than hours.

According to [122], paths with more choice points, intersections or simply turns are considered more complicated than paths with fewer turns. This is a natural consequence of the fact that there is a higher chance of error. More interestingly, they state that paths with more turns are perceived to be longer as well.

Holscher et al. [116] explored the various strategies that people use in exploring multi-storey buildings. The first strategy shown by Kuipers et al. [123] stresses on the primacy of a set of central paths or a *route skeleton* in way finding. People explore along this central route skeleton. Another strategy referred to as the *horizontal position strategy* was rarely used by people and was generally not very efficient. Here people try to get to the correct horizontal location first. Following this they try to find the way to the correct floor. The reduced efficiency of this strategy was a natural consequence of the fact that the experiments in the paper were conducted in a building where each floor was different from the next. The last strategy which was used by more experienced participants and was also proved to be the most efficient is what was called the *floor first strategy*. As the name suggests, this strategy involved the person trying to get to the required floor first and then exploring horizontally to find the goal.

O'Neill [124] studied the accuracy of simulated environments in studying way-finding behavior. Their approach was to examine behavior in a simulated environment and compare it to results from actual experiments. Their findings showed that human behavior in simulated environments reasonably mimicked real life. Montello et al. [125] had a much more comprehensive analysis of the effect of different sources: maps, virtual environments and real world experience. In general, the more immersive the environment the less difference there is from real life.

6.3 Experiment Performed

In order to understand more about how humans explore environments and store spatial knowledge, we created a game that requires exploration and way-finding and analysed how the game was played. The environment must have some degree of complexity or diversity to be engaging and invite exploration [126]. To reduce development effort and to allow for flexibility in environment creation, we built the experiment inside the popular game Minecraft.

6.3.1 The minecraft gaming environment

Minecraft [127] is a java based multi-platform sandbox construction game. The game involves players creating and destroying various types of blocks in a three-dimensional environment. In the original game, the player takes on an avatar that can destroy or create blocks, forming buildings, structures, artwork and even entire cities on multi-player servers or single player worlds across multiple game modes.

In the original game players can break any block and build any block provided, he/she has the resources. In the work for this paper, we used an existing plugin [128] that constrained players so that they could only move around in the environment and interact with doors and switches i.e. elements that were essential for the experiment. A second modification was created [129] to keep a log of the movements and actions of the players and store them in a MySql server for analysis. The following sections describe the game, the methodology used for analysis and some of conclusions from the experiments.

6.3.2 The game

The literature review covered some different ways in which simulated environments have been used for studying human spatial knowledge. These simulated environments ranged from VR environments to very simple games of finding a way through a maze.

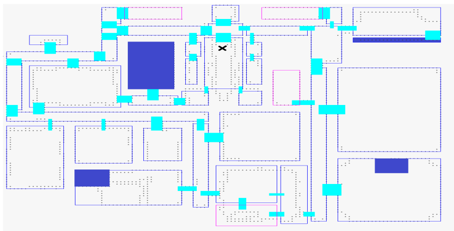
Most experiments tried to constrain the first part of knowledge acquisition. A typical example is Melinger Knauff and Bulthoff [109] who ensured that all particiapnts got indentical stimuli in order to be able to fairly compare secondary task comparison. So participants watched a video rather than actively navigating through the environment. This has resulted in there being very little existing literature on how people actually explore environments; also, we believe that the paths taken during exploration could also reveal interesting aspects of human exploration.

The premise of the game is that player has been teleported into an old abandoned palace where eleven people have been imprisoned in different locations spread over the three storey environment. The objective of the game is for the player to free the eleven prisoners and subsequently follow instructions to open the main gate to the palace and escape. The palace is a three storey building with 44 rooms modified from an existing Minecraft map [130]. The layout of each floor of the palace is shown in Figure 6.1. A player joining the server is spawned at the location indicated on the map with an X. During the first few minutes the player is presented with the story line and interactively told how to use the controls and play the game and free the first prisoner. Subsequently, the player is tasked to find and free the other prisoners. The locations of the prisons, as shown by the shaded areas in the map, are spread all over the building. This is the first phase of the game and we call this the *exploration phase*. This phase requires the player to move around and explore the building. This phase can be reasonably equated to what a new visitor to a building (e.g., shopping mall) experiences.

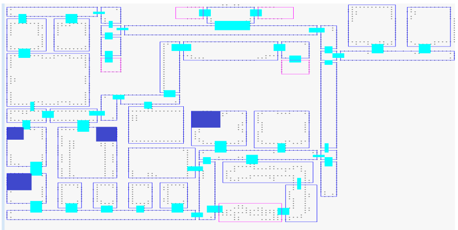
The next phase, which we call *knowledge testing phase*, starts when the eleventh prisoner has been freed. During the phase, the cognitive map formed by the player is tested through a series of three tasks. By not revealing the nature of the second phase to the player at the beginning of the game and also by hiding the location of the knowledge testing tasks, we ensure that the player does not make a special effort in remembering locations which could artificially alter the cognitive map formed.

When the eleventh prisoner is freed and the exploration phase ends, the player is given instructions to proceed to the gallery room in the building. This room would have been examined by the player during exploration. It is the only room in the palace whose walls are covered with paintings and this makes it reasonably likely that the player will remember this location because of its *perceptual salience* [46].

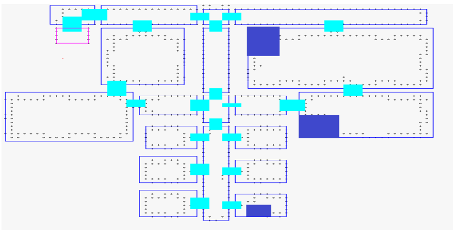
Once the player locates and presses the switch that is revealed in this room, the player is given instructions to the second floor library. There are two important factors for having this particular location. Firstly, the library has four entrances and is very likely that the player would have entered this room multiple times during the exploration phase. Secondly, being on the second floor, there are multiple paths to this location from the gallery as can be seen in figure 6.2. Preference



(a) Ground Floor



(b) First Floor



(c) Second Floor

Figure 6.1: Floor Plans of the three floors. The X indicates the starting point. The blue color indicates the prisoner locations.

for a particular route among players would help understand more about his/ her cognitive map.

Once the player finds this location he is given the final instruction to proceed to his starting location to find the final switch that will open the main gate to the palace. Again, there are multiple routes to this location some of which are significantly shorter than others. Also, being a starting location and in a somewhat central location the location will likely have been frequently visited and will have some *cognitive salience* [46].

The player locations at different times and the time at which each prison was opened and the time taken to complete each task in the testing phase were all recorded. The next section outlines the details of the experiment itself.

6.4 Experiment details

There were 50 participants in all. Each participant was given five minutes to get used to the controls of the first person game which involved using both the mouse and the keyboard: W, A, S and D keys for movement and the mouse for looking around. A single click on the mouse would allow the player to interact with the environment by either opening doors or prisons. The players were given 45 minutes to complete the game. Of the 50 participants, the data from only 44 participants were used, the remaining six experienced motion sickness from the movement in the first person gaming environment and had to quit playing before the game could be completed.

6.5 Analysis of Experiment Results

In this section we introduce some of the metrics that were used for analyzing movement in order to understand the role that memory plays in exploration.

6.5.1 Calculation of random walks

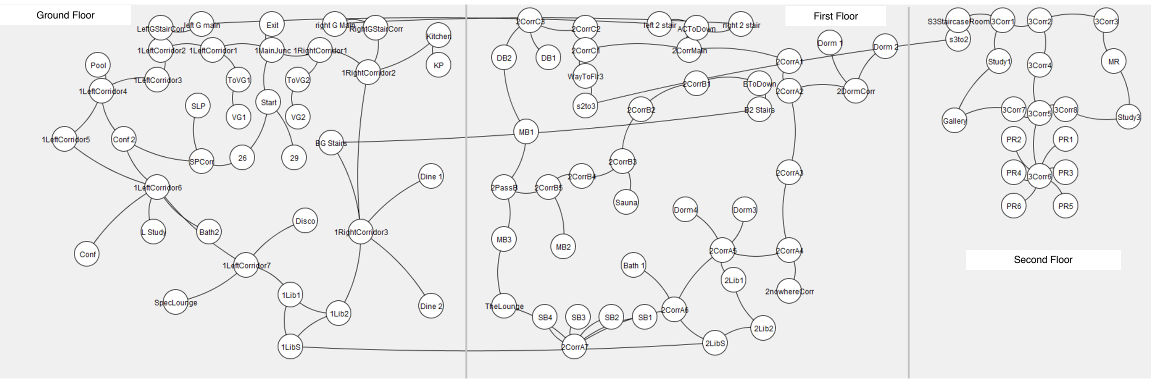


Figure 6.2: Room Layout Graph

A random walk is used as a benchmark for comparison. This random walk is done on the undirected graph shown in Figure 6.2 which is a graphical illustration of the aggregated floor plans from Figure 6.1. Each iteration of the random walk is performed until the walker covers 100 percent of the environment. A collection of random walks is obtained until the variance in the radius of gyration of generated graphs stabilizes.

6.5.2 Room visit frequencies

We first calculated the frequency of visits for each room per player and compared this against the random walker. This is a simple test to determine if the players have a pattern or strategy in their exploration.

6.5.2.1 Calculation

For any room r, let $f_p(r)$ be the number of times a player visited r and let $f_{rw}(r)$ be the number of times a random walker visited the same room. Then the normalized number of visits by a player to the room can be obtained as:

$$y(r) = \frac{\alpha_p(r)}{\alpha_{rw}(r)} \tag{6.1}$$

Where

$$\alpha_x(r) = \frac{f_x(r)}{\sum_{a \in R} f_x(a)} \tag{6.2}$$

Figure 6.3 shows the value of $y(r)$ each room as a scaled version of Figure 6.2. Red color indicates a y value of greater than 1.05 and the green color indicates a value of less than 0.95. The diameter of each node in this graph is scaled to $y_r \times (\textit{unscaled diameter})$.

This implies that, a white color indicates that the normalized number of visits is the same in both random walk and in the data. A value greater than 1 indicates that players visited the more than the random walker and smaller value indicates the opposite. It is hard to discern any pattern in this data other than that the amount of time spent on the third floor is higher than the number of visits on the second floor which is more than the number of visits on the first floor.

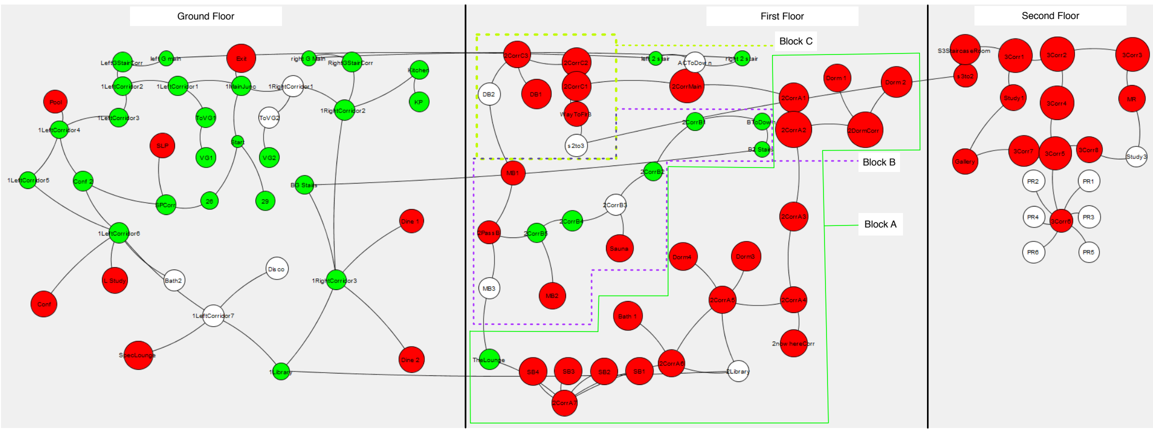


Figure 6.3: Map scaled by normalized number of visits

As it can be clearly seen that players seem to have a lot more visits on the third floor, we decided to normalize to number of visits on the floor rather than the total number of visits. On doing this, if the graph turned out to be different, it would seem that unlike a random walker, a player differentiates between a simple link between rooms or corridors and a staircase which is a link between floors. Figure 6.4 is the floor normalized version of Figure 6.3.

6.5.2.2 Discussion

The figures in this section provides a possible validation of a variation of the floor first strategy [116] used for exploration. The strategy in the original paper was for way-finding, but here it seems to be being used for exploration. The players seem to consider each floor as a separate entity and are generally reluctant to take the staircase. This is also because the process of separating each floor helps in bringing some organization and structure to the confusing room layout and the process of exploration (i.e., completely explore one level before the next).

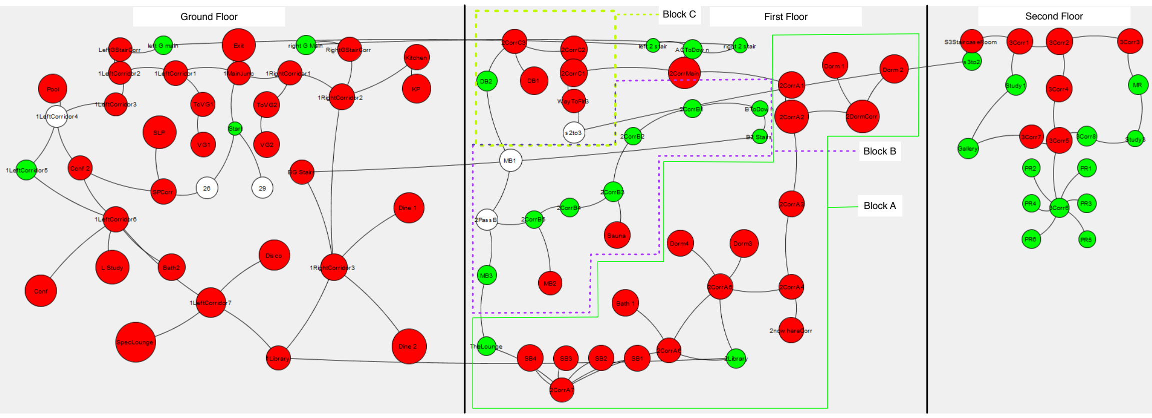


Figure 6.4: Map scaled by floor normalized number of visits

The existence of this floor first strategy is further demonstrated by the low visit frequencies to Block B on the second floor. Block B on the second floor is accessible in three possible ways, through a staircase in the first floor and through rooms DB2 and The Lounge in Block A and C respectively. This means that Block B is not accessible via direct corridor from the same floor like Block A and C. The only obvious way is by going down a floor.

6.5.3 Markov data analysis

In this section we conduct an analysis of the recorded player data in comparison to biased and unbiased random walkers. The purpose is to investigate the role that memory plays in the exploration of the environment. First we conduct a Markovian analysis of the player data collected to understand the role of memory in the efficiency of the exploration process.

We take an m^{th} order Markov model to represent an m-step memory of the explorer, where steps constitute room visits. One way to speculate on the size of the memory used by a human during exploration is to predict a path of length n from some Markov data of order $m < n$.

In an m^{th} order Markov model, the basic idea is the action at any point of time depends only on the previous m actions. By assuming that the process of exploration is an m^{th} order Markov process, we are hypothesizing that the next room that is visited by a player is only dependent on the previous m steps. This is different from a simple random walker that tries to avoid the previous m rooms. Since the next step is dependent on the actions of players who have visited that same subsequence of m rooms, the Markov model theoretically encapsulates other factors like layout, visibility, etc. The methodology of doing this Markovian analysis is explained in more detail in Section 6.5.3.1.

We then try to understand if an m^{th} order Markov model is sufficient for describing exploration efficiency. We do this by measuring the exploration performance in terms of minimum hops needed and maximum coverage obtained for

Table 6.1: Summary of symbols and their meaning

Symbol	Meaning
$Pr(A\|B)$	Probability of occurrence of event A given event B
X_n	Random variable indicating the location in the n^{th} step
$p_{ij}^{(n)}$	Probability of going from state i to state j in n steps
R	Set of all rooms
r	A particular room
N_r	Set of neighbours of room r
$P^{(n,D)}$	Set of all paths of length n in dataset D
$Q^{(n)}$	Random variable representing a path of length n
$q^{(n)}$	A particular path of length n
$\phi(a, S)$	The frequency of element a in set S
$x_i^{(q)}$	i^{th} location in a particular path q

different values of m and comparing this with the exploration of a random walker and an agent-based model that uses a simple memory rule for exploration. Interestingly we find significant performance improvements when we reach m of 6 to 8.

6.5.3.1 Calculation of markov data

This section explains how the aforementioned Markov calculations are done. These calculations are performed on the data that was derived from the experiments in Minecraft. This data is stored in the form of a directed graph with each node corresponding to a room and a directed edge indicating the movement of the player from one node to the next. Each edge also stores the time of traversal.

The n^{th} order Markov probability of visiting a room b from a room a is defined as the probability that the n^{th} room after visiting room a is room b. Mathematically, it can be stated as:

$$p_{ab}^{n} = Pr(X_n = b|X_0 = a) \tag{6.3}$$

It is assumed that it is a time homogeneous process, i.e.,

$$p_{ab}^{n} = Pr(X_{k+n} = b|X_k = a) \; where \; k \geq 0 \tag{6.4}$$

We can calculate the n^{th} order Markov data of a particular dataset using the following :

1. For each path of length n, the number of times that path is observed in dataset D. This can be directly counted from the dataset. From this, equation 6.5 can

be used to derive p^n_{ab}:

$$p^n_{ab} = \frac{\left|P^{(n,D)}_{ab}\right|}{\sum_{x \in R} \left|P^{(n,D)}_{ax}\right|} \tag{6.5}$$

2. For each path of length n, the likelihood that a particular path is the result of n steps being taken. From the frequency data, it is possible to generate the likelihoods using the following calculation:

$$Pr(Q^{(n)} = q^{(n)}) = \frac{\phi(q^{(n)}, P^{(n,D)})}{|P^{(n,D)}|} \tag{6.6}$$

3. We finally calculate the the probability of any destination given a particular path of length n. Mathematically, this gives $Pr(X_{n+1} = r|q^{(n)}) \forall r \in R$.

Given the probability of any destination, given a particular path of length n, it is possible to predict the $(m+1)^{th}$ step given the previous m steps i.e. the 1^{st} to m^{th} step. Following this, the $(m+2)^{th}$ step can be predicted by doing the same calculation using the previous m steps from 2 to $m+1$. Thus any path of length n can be extrapolated from an m^{th} order data.

6.5.3.2 Types Of Exploring agents

To evaluate the role of memory in exploration by comparing the exploration performance of the following:

- *Actual Players*: This is the average over the actual paths taken by all the players.
- *Markov Agents*: These agents explore the environment using the calculations explained in Section 6.5.3.1. As explained there, the action of an m^{th} order markov agent at a particular point in the path is a function of the actions of the actual players who had taken the same m steps. The calculations are performed for m from 1 to 13. We present further analysis on the validity of this calculation in the appendix.
- *Unbiased Random Walker*: The next move is chosen by this agent is chosen randomly with equal probability.
- *Agent with m-step Memory*: In this, the agent is assumed to have a m-step memory. It moves exactly like the random walker except that it avoids moving back to any of the m rooms it visited previously. If there is no unvisited room, the agent checks it's m-step memory for an unvisited junction. If such a junction exists, it goes back to that point and continues exploring. If such a junction does not exist, then the agent choses a location at random with equal probability.

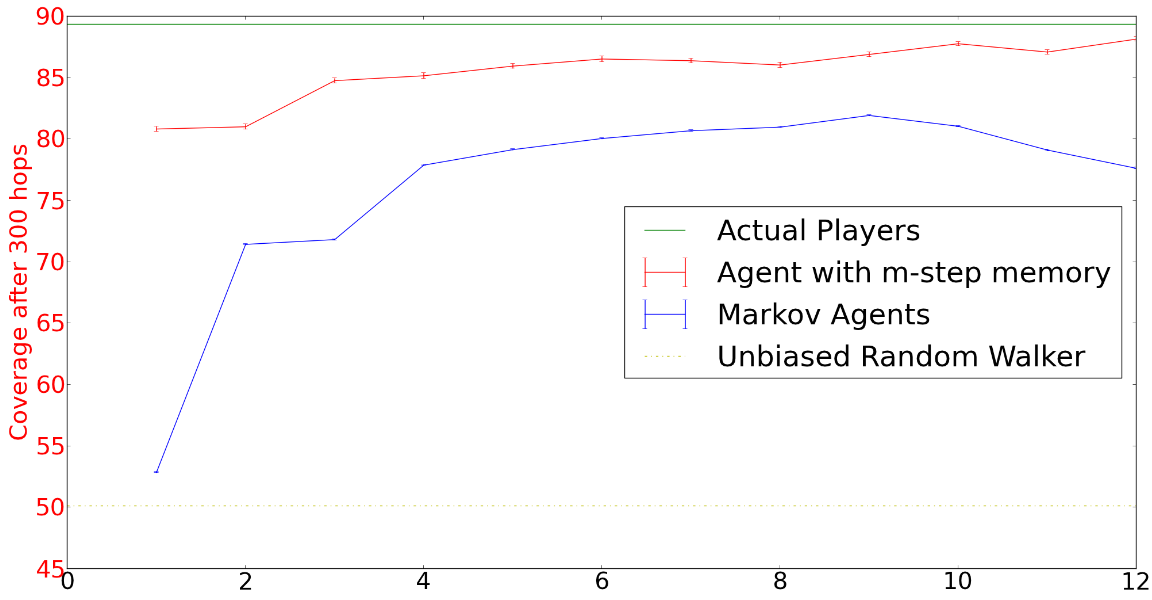


Figure 6.5: Coverage for 300 hops

6.5.3.3 Expected Coverage Given Number Of Hops

The average coverage after a given number of hops gives an estimate of the efficiency and effectiveness of exploration. Figure 6.5 shows the coverage of the four agents explained in Section 6.5.3.2 after 300 hops.

The figure seems to indicate that even a second order Markov agent i.e. one whose next position is only dependent on it's current and previous position performs much better than an unbiased random walker. It also seems to indicate that after 300 hops the performance of the actual players are much better than both the Markov agent and an agent with simple m-step memory. This is not surprising since, it is likely that when nearing 300 hops, the long term memory of the player also has a major influence. As mentioned in section 6.2, in the slightly longer term, the walker would probably have formed a route or some sort of survey knowledge and this will include the structure of the building, routes and short cuts and, in general, more structure to the mental map. The fact that the Markov agent performs worse than the agent with memory regardless of the value of m agrees somewhat with this conclusion. However, this could also because the Markov agent has the same errors as the collective human memory - whereas the m-step agent has perfect memory.

6.5.3.4 Expected Hops Given Coverage

We also calculate the minimum number of hops required to obtain a given coverage. It gives a more granular measure than coverage for a given number of hops. The average final coverage for a player after the exploration phase of the game is 89 ± 1 as shown in Figure 6.5. We first calculated the minimum number of hops required by the different agents to obtain this coverage (Figure 6.6a). This graph shows the number of hops required by different types of agents for getting this coverage. This graph shows the same pattern as discussed in Section 6.5.3.3.

It is interesting to see how the graph is for 50% coverage. By this point it is unlikely that long term memory will have much of an effect. Figure 6.6b shows the results of this calculation. The magnitude of the difference between hops required in for 50% and 88% shows a non linear increase indicating that exploration becomes progressively more difficult. The figure also shows that agents with a simple memory of 5 or more steps seem to perform at the same level or better than humans. It is also interesting to note that the performance Markov agents however, still perform worse than agents with a simple m-step memory probably because of the imperfect nature of the short term human memory on which it is based. The gap in performance between the markov agent and the actual player is quite narrow at $m = 7$ to 9. This indicates that the room visited at any point can be reasonably predicted from the previous 6-8 rooms during this early phase of exploration. However, the fact that the gap exists indicates that this is probably not sufficient to reproduce human exploration.

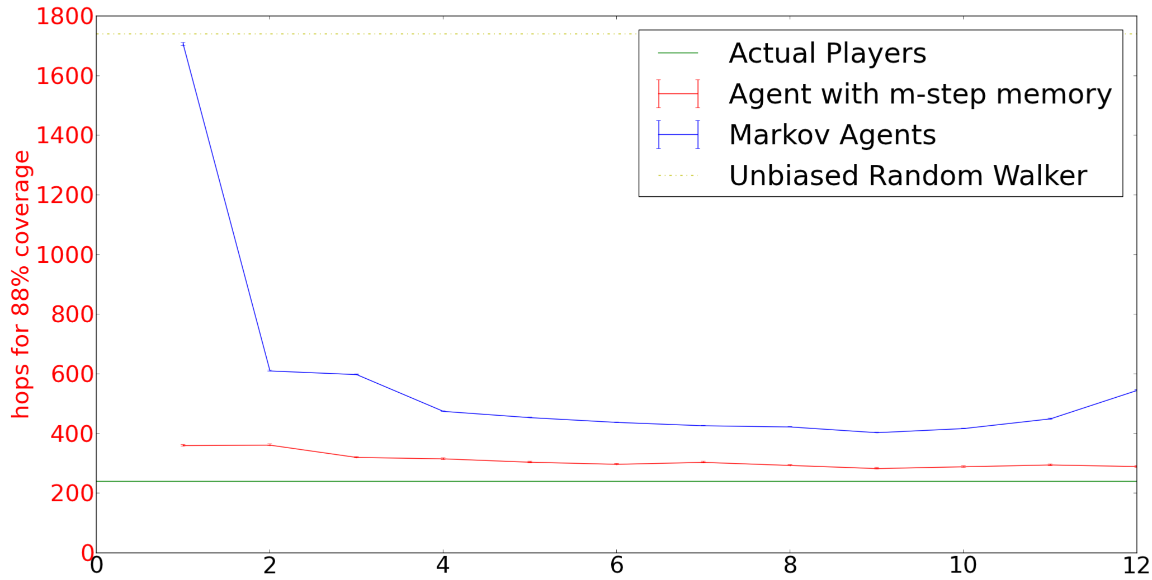
6.5.4 Empirical Analysis

We performed a empirical and qualitative analysis of the actions of the players at different locations. This analysis revealed the existence of definite decision points, patterns in exploration and the importance of cues in recognition and memory.

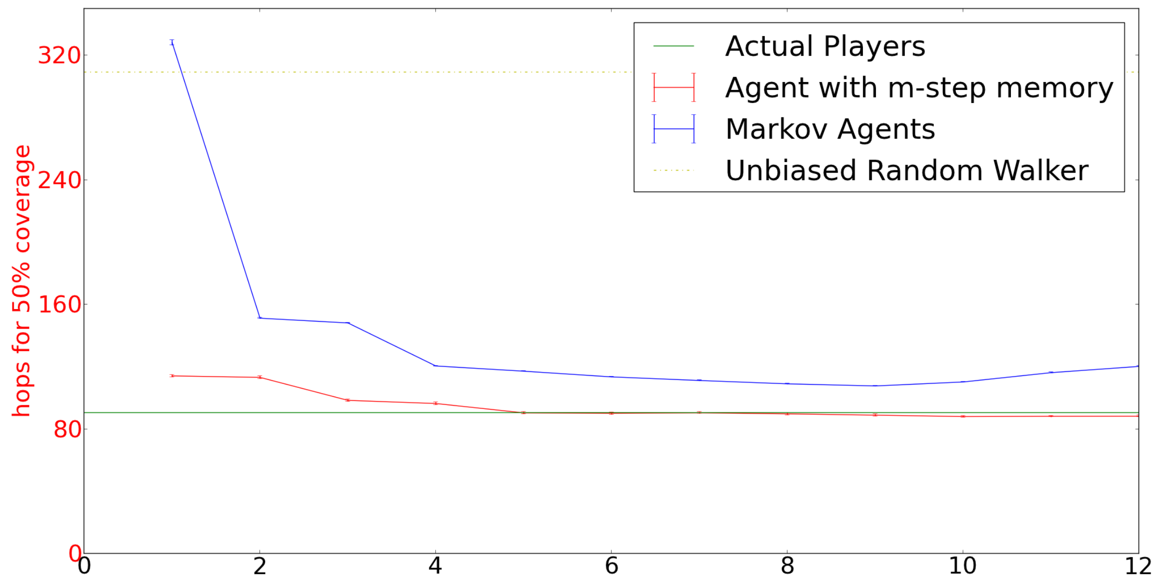
6.5.4.1 Existence of decision points

Figure 6.7 illustrates the decisions of people at different types of rooms and corridors, where it is possible for them to make a decision. At certain locations, such as corridors that have no rooms on the side (i.e. they are simply connections between two areas), staircases and simple corners, the only decision that a player can make is whether to move forward or turn back. Turning back would require a conscious decision by the player. A pure random walker would generally have an equal chance of going back or forward. As clearly shown in figure 6.7, the data reveals that players generally avoid such decisions.

What is more interesting is the behavior of people at rooms which have just two doors. The data seems to reveal that if the opposite door is clearly visible from one door, then the room is used by the player almost exactly like a corridor, though there is a slightly higher chance of turning back. However, if the opposite door is not visible, then there is a roughly 50-50 chance of the person taking that other door or going back.



(a) Hops for 88% coverage.



(b) Hops for 50% coverage

Figure 6.6: Minimum hops required for obtaining given coverage

6.5.4.2 Location recognition and memory

In the game environment, there exists a corridor that seems to reveal an interesting aspect of memory and exploration. The layout of this corridor is shown in Figure 6.8. The corridor labeled *Dorm Corridor* is interesting because it is connected to the main Block A corridor only at one end and the two rooms on this corridor (D1 and D2) do not have a prison, a staircase, or any connections that make it at all relevant to the player. However, it lies on a commonly used corridor and is thus often passed by by every player. In an ideal scenario, players would remember this fact and never visit *Dorm Corridor* after the first visit to the junction labeled *A2*. However, as Figure 6.9 indicates, during the task completion phase, regardless of the number of times the junction is visited during exploration (on average around 2-7 times per

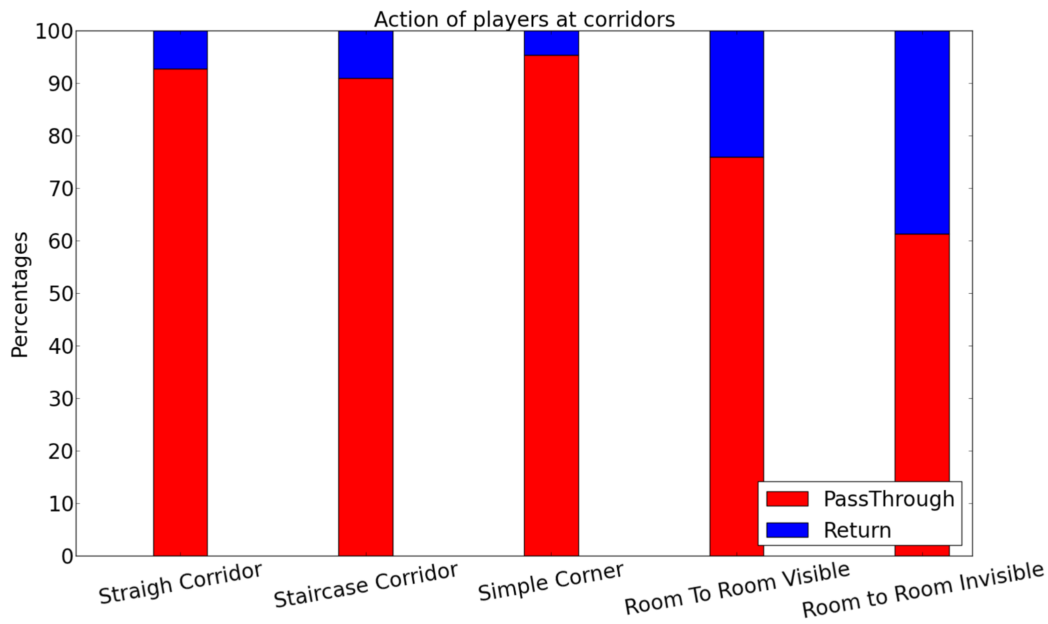


Figure 6.7: Behavior at simple corridors. There are definite decision points during exploration

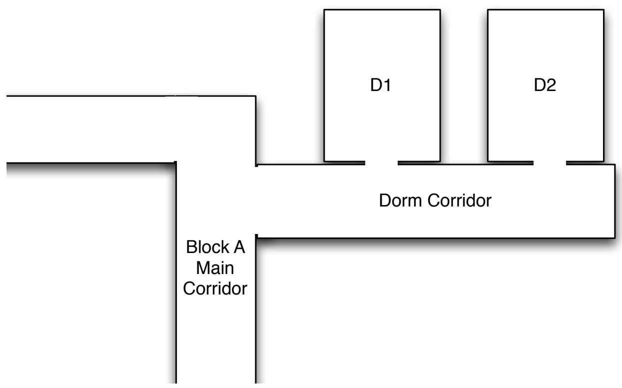


Figure 6.8: Layout of the relevant corridor

player), players almost always turn into the *Dorm Corridor*.

At first this leads to the conclusion that the players never learn and have no memory. However, a similar analysis of movement after entering *Dorm Corridor* indicates that this isn't the case. As shown in Figure 6.10 indicates that around 80% of the players head right back to the junction after entering this corridor. This probably indicates that the context given by the location of signs and doors in the corridor helps the player remember the corridor, it's location and it's uselessness.

6.6 Conclusion

In this paper, we presented a novel game-based methodology that allows for experimental investigation of human navigation and exploration. Although similar method-

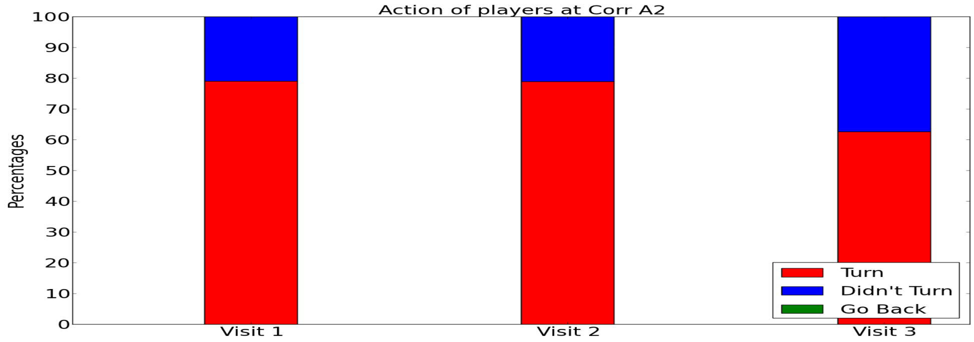


Figure 6.9: Behavior at *junction A2* during tasks

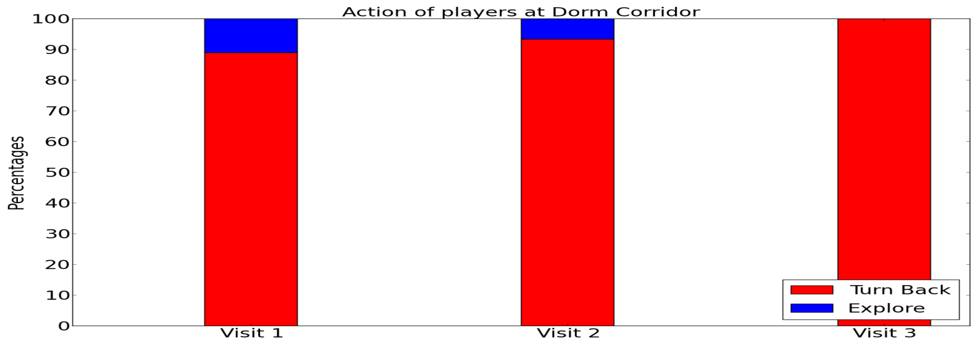


Figure 6.10: Behavior at *Dorm Corridor* during tasks

ologies have been used to understand more general crowd behaviour, we believe this is the first case in which quantitative analysis of a game has been used to understand memory in exploration. The Markovian analysis of the players movement in the game revealed a number of significant findings. Firstly, we showed that a simple memory model, with a depth of between 6-8, is sufficient to approximate a 'human level' of exploration efficiency. This was consistent in two measure of exploration efficiency, total coverage from a fixed number of hops and the number of hops required to obtain a fixed coverage. The memory depth of 6-8 seems to be consistent with well known studies of human memory capacity. The experiments also highlight the importance of junctions in the exploration process, in particular that decisions (i.e., changing course) seem to almost exclusively occur at junctions. Explorers also try to reduce the number of decisions they have to make by proceeding to the next clearly visible room or corridor if only one such is visible. The results go on to show that people seem to explore environments using a floor-wise strategy, where they are reluctant to move to a different floor until they have finished exploring the current one. Finally, we take particular environmental structures to show that easily recognisable locations can improve exploration efficiency by effectively removing sub-graphs of the room network.

The simple agent-based memory model developed in the paper is shown to approximate human-like efficiency in its exploration strategy. We think this type of simple model is an excellent starting point for developing agent-based models that can be used to evaluate safety-by-design architecture in complex structures. We see the experiments and methods presented here as a starting point for further investigations into the role of exploration and memory in human egress. Similar experiments could be conducted to evaluate the role of long-term memory in exploration, and perhaps validate the three-stage map building of Siegel and White [112].

Chapter 7

Quantitative Comparison Between Crowd Models for Evacuation Planning and Evaluation

Crowd simulation is rapidly becoming a standard tool for evacuation planning and evaluation. However, the many crowd models in the literature are structurally different, and few have been rigorously calibrated against real-world egress data, especially in emergency situations. In this paper we describe a procedure to quantitatively compare different crowd models or between models and real-world data. We simulated three models: (1) the lattice gas model, (2) the social force model, and (3) the RVO2 model, and obtained the distributions of six observables: (1) evacuation time, (2) zoned evacuation time, (3) passage density, (4) total distance traveled, (5) inconvenience, and (6) flow rate. We then used the DISTATIS procedure to compute the compromise matrix of statistical distances between the three models. Projecting the three models onto the first two principal components of the compromise matrix, we find the lattice gas and RVO2 models are similar in terms of the evacuation time, passage density, and flow rates, whereas the social force and RVO2 models are similar in terms of the total distance traveled. Most importantly, we find that the zoned evacuation times of the three models to be very different from each other. Thus we propose to use this variable, if it can be measured, as the key test between different models, and also between models and the real world. Finally, we compared the model flow rates against the flow rate of an emergency evacuation during the May 2008 Sichuan earthquake, and found the social force model agrees best with this real data.

Crowd simulation is an area that has been the subject of a significant amount of multidisciplinary work over the last few decades [2? ?]. Its applications range from simulating crowds for movies [3, 4] and games [? ?] to analyzing pedestrian behavior [5? , 6] and preparing for fire evacuations and similar emergencies [7? ?]. The earliest attempts to simulate crowds generally adopted a macroscopic approach [53, 61], where there is no explicit notion of an individual. Later, with increasing computational resources and with availability of observational data on an individual level [? ? ?], modelers were able to develop microscopic approaches [4?] for application in areas where it was necessary to model and analyze individuals in the crowd. For example, in a simulation of evacuation, knowledge of the movement of crowds could reveal methods to improve crowd flow and evacuation speed.

One of the earliest and seminal works in individual-based motion planning was Craig Reynolds's model of coordinated animal motion such as bird flocks and fish schools [4]. Okazaki and Matsushita [95] assigned magnetic poles to goals, agents and obstacles to model movement. Subsequently, Helbing's Social Force Model [?] was developed, which is still one of the most popular models of movement in crowds. More recently, there have been several velocity-based approaches to motion planning, such as the synthetic vision based model [131] and the Reciprocal Velocity Obstacle Model [83, 132, 133].

The advocation of simulation-based analysis has become increasingly common over the last decade. Some well know applications include analysis of the yearly Muslim Hajj [?], or more recently the Love Parade disaster, Germany 2010 [?]. In the case of the latter, models and expertise had been used to guarantee the safety of the event, only for unforeseen circumstances to result in the deaths of 21 individuals. Clearly these real world examples emphasize the critical role that crowd modelling plays in safety preparation and planning, this in turn emphasizes the need for understanding the model dynamics, limitations and similarities. The extent to which these models are capable of accurately predicting the motion of a crowd is therefore critical for planning and safety.

Ideally these models should be validated against real-world data from all scenarios, for all cultures and for all varieties of crowd composition. Unfortunately real world data regarding egress or emergency situations is limited, often incomplete (the initial conditions are hard to know) and certainly not controlled. Even in the rare circumstances where data is available this often describes measurements and phenomena at the macro-scale, e.g., flow, density, average speed, etc. Because these models of individuals exhibit emergent behaviors at the mesoscopic and macroscopic scales, it is in general hard to tell whether the dynamics at the individual level are correct. The best researchers can realistically hope for is to collect microscopic data for a single scenario to calibrate the model. An alternative approach to the data-intensive one is to instead look quantitatively at the fundamental dynamics of the models and understand where these models differ, at the same time identifying common aspects of the models. This will aid in understanding fundamental aspects of all crowd models and offer insight into real-world dynamics of human crowds.

While much of the existing research does offer basic comparison of proposed models with existing models to demonstrate their usefulness, there is no existing quantitative comparison of the differences and similarities of these models to tell which is most accurate. The objective of this paper is to demonstrate a methodology for quantitative comparison of simulation models in a simple egress simulation. For this, we choose three popular models that are structurally very different. Since our focus is on the comparison methodology, we do not worry about specific versions of the models, in particular recent modifications and enhancements that are supposed to produce more realistic crowd behaviors.

The contribution of the paper is then three-fold: firstly, the analysis and comparison of these models provides interesting insight into the consequence of adopting each in particular forms of crowd or egress simulation. Secondly, the systematic approach we describe could be used in future to compare further models and develop a standard method of comparison for crowd simulation. Finally, the paper conclusion identifies a single measurable metric that is most effective in distinguishing the behaviour of the models.

The remainder of this paper is organised as follows. The models that are consider in the comparison are first described in Section 7.1; Section 7.2 describes the experiments that were conducted and the methodology for analysis. Significant observations from the simulations are presented and analyzed in Section 7.3. Finally, Section 7.4 concludes the paper.

7.1 Models

In this section we describe the three individual (or microscopic) models that are compared in this paper. We use the general term agent to refer to individuals within each of the models. The lattice gas model is a probabilistic approach where the future location of an agent is probabilistically determined based on the current configuration of its neighborhood. This implies that the same initial configuration can produce different results during different runs. On the other hand, in the social force model and reciprocal velocity obstacle model, agents find their ways to their destinations via deterministic collision-avoiding calculations. As a result these models produce the same result on multiple runs for a particular initial configuration.

7.1.1 Lattice gas model

A Cellular Automation (CA) model is one in which space and time are discrete. Furthermore, the state space of a CA model is also discrete and finite. In each time step the values of all cells are updated synchronously based on the values of cells in their neighborhoods. Depending on the type of neighborhood (i.e., von Neumann, Moore), and the type of lattice (triangular, square, hexagonal, etc.), the exact number of cells in the neighborhood of a given cell can vary [**?**]. Lattice gas models are CA models that make use of a discretized version of the Boltzmann transport equation to model motion [64**?** **?**]. Advances in this modeling area include the Extended

Floor Field Model [?] in which agents interact through virtual traces that act like the pheromones in chemotaxis, and the SWARM information model [65] which uses multiple floor fields to model transmission of knowledge between agents. In this study we use the model by Tajima and Nagatani [?]. In contrast to later CA models with additional features like bi-directional movement [?] and vision impairment during evacuation [?], this original model is simple, and adequate for our model comparison purpose.

A square grid is used, and each cell can be occupied by at most one person. The person performs a random walk biased towards the single exit in the room. For example, in Fig. 7.1(a), the probability that the person takes a step in the $+y$ direction is $P_y = (1-D)/3+De_y/(e_x+e_y)$, while the probability that it takes a step in the $-x$ direction is $P_{-x} = (1-D)/3 + De_x/(e_x + e_y)$, since the intended direction $\vec{e}$ has positive projections along the $+y$ and $-x$ directions. Along the $+x$ direction, for which $\vec{e}$'s projection is negative, the probability that the person takes a step in the $+x$ direction is $P_x = (1 - D)/3$. Here we see that the random walk probabilities contain an unbiased component $(1 - D)/n$, which is the same for all n permissible directions (in the Tajima-Nagatani model, the $-y$ direction is not permitted), as well as a biased component $D = 0.7$ that favours movement towards the exit.

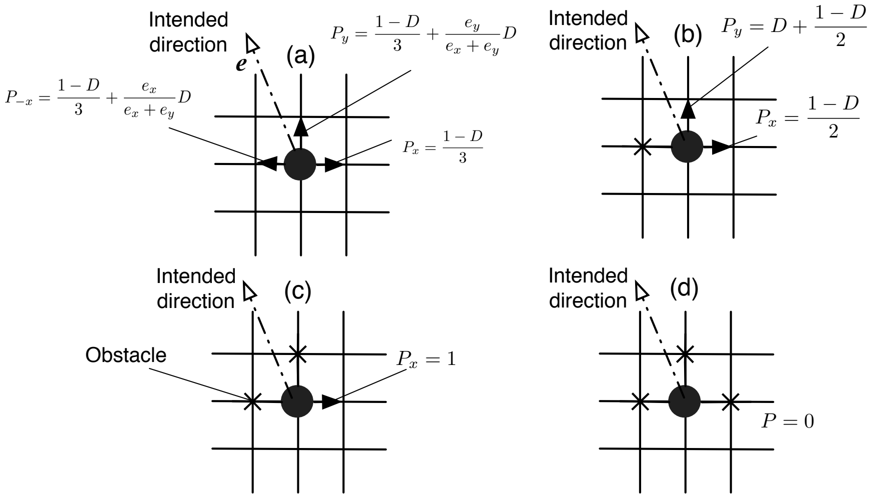


Figure 7.1: Four out of eight possible configurations of a walker on the square lattice moving towards an exit in the direction $\vec{e}$ shown: (a) unobstructed walker, (b) walker obstructed to the left, (c) walker obstructed to the left and top, and (d) completely obstructed walker.

7.1.2 Social force model

The social force model is one of the most popular models for motion planning in crowds [96, 134, 135]. This model is based on the idea that pedestrians move in response to fictitious attractive or repulsive *social forces* produced by obstacles and other pedestrians. Over the years, several extensions have been made to the social forces model like the modeling of grouping behavior [96]. In this paper, we use the Helbing-Molnár-Farkas-Vicsek (HMFV) social force model [?], which is tweaked from the original model introduced by Helbing and Molnar in 1995. In the original model

$$m_i \frac{d\vec{v}_i}{dt} = \vec{f}_i + \sum_{j(\neq i)} \vec{f}_{ij} + \sum_{W} \vec{f}_{iW} \tag{7.1}$$

proposed by Helbing and Molnar [?], three types of forces act on a given agent i with mass m_i, instantaneous position $\vec{r}_i(t)$, and instantaneous velocity $\vec{v}_i(t)$. The first is a restoring force

$$\vec{f}_i = -m_i \frac{\vec{v}_i - \vec{v}_0}{\tau_i} \tag{7.2}$$

that steers the agent towards the desired velocity $\vec{v}_0$ at a rate determined by the characteristic time $\tau_i = 1$. Here

$$\vec{v}_0 = (1-p)V_0\vec{e}_i(t) + p\left\langle \vec{v}_j \right\rangle_i, \tag{7.3}$$

where V_0 is the preferred speed, $\vec{e}_i$ is a vector that points towards the exit, and $(1-p)$ is the weight given to this desired velocity. With a weight of p, agent i also adapts to the average velocity $\left\langle \vec{v}_j \right\rangle_i$ in its neighborhood. When p is small, agent i moves more along its intended direction $\vec{e}_i(t)$, whereas if p is large, agent i tends to follow where its neighbors are going. We can therefore tune p from $p \approx 0$ (self-directed normal egress) to $p \approx 1$ (panic-driven herding during emergency evacuations). In this paper, we used $p = 0.2$ to simulate an emergency evacuation situation.

The second is a repulsive force

$$\begin{aligned}\vec{f}_{ij} = &\{Ae^{(R_{ij}-d_{ij})/B} + k\eta(R_{ij} - d_{ij})\}\vec{n}_{ij} \\ &+ \kappa\eta(R_{ij} - d_{ij})\Delta v^t_{ji}\vec{t}_{ij},\end{aligned} \tag{7.4}$$

where

$$\eta(x) = \begin{cases} x, & \text{if } x \geq 0; \\ 0, & \text{if } x < 0 \end{cases} \tag{7.5}$$

that mimics the *psychological tendency* of agents i and j to move away from each other if they are too close. Here $R_{ij} = R_i + R_j$ is the sum of radii of the two agents, $d_{ij} = |\vec{r}_i - \vec{r}_j|$ is the physical distance between the two agents, and $\vec{n}_{ij} = (n^1_{ij}, n^2_{ij}) = (\vec{r}_i - \vec{r}_j)/d_{ij}$ is the unit vector pointing from agent j to agent i. Additionally, $A = 2000$ N and $B = 0.08$ m are the repulsion coefficient and the fall-off length of interacting agents respectively [136]. Helbing and Molnar also found it necessary to introduce two other terms in the interaction force when agents i and j are in contact with each other, i.e. $d_{ij} < R_{ij}$. This counteracting body compression term $k\eta(R_{ij} - d_{ij})\vec{n}_{ij}$ and sliding friction term $\kappa\eta(r_{ij} - d_{ij})\Delta v^t_{ji}\vec{t}_{ij}$ are crucial for getting realistic behaviors of panicking crowds. Here $\vec{t}_{ij} = (-n^2_{ij}, n^1_{ij})$ is the tangential direction and $\Delta v^t_{ji} = (\vec{v}_j - \vec{v}_i) \cdot \vec{t}_{ij}$ is the tangential velocity difference.

Finally, in the third force

$$\begin{aligned}\vec{f}_{iW} = \left\{A_i e^{(R_i - d_{iW})/B_i} + k\eta(R_i - d_{iW})\right\} \vec{n}_{iW} \\ - \kappa\eta(r_i - d_{iW})(\vec{v}_i \cdot \vec{t}_{iW})\vec{t}_{iW},\end{aligned} \tag{7.6}$$

the first and second terms repels agent i from a wall that it is d_{iW} away from, while the third term (which is negative) is introduced to mimic the observation that people move faster near walls when they are in crowded situations. Here, $\vec{n}_{iW}$ is the normal vector of the wall, and $\vec{t}_{iW}$ is the tangent vector of the wall. Also, $k = 12,000$ kg/s^2 and $\kappa = 24,000$ kg/ms are respectively the body force constant and the sliding friction force constant used.

7.1.3 Reciprocal velocity obstacles model

The third model we consider is the reciprocal velocity obstacles (RVO) model. In this model, the time to the next collision is calculated based on the relative velocities of N agents. Each agent then changes its velocity $\{\vec{v}_i\}^N_{i=1}$ to maximize this time to collision. By continuously updating the velocities in this manner, collisions are avoided. This algorithm was first proposed by Fiorini et al. [137], but was first used in multi agent systems in [97]. Since then there have been several modifications and improvements to the algorithm [6, 82, 83, 138], although the underlying idea remained the same. In this paper, we use the RVO2 model introduced by Guy et al. [83], where the collision avoidance computation is based on computational geometry and linear programming.

Given a preferred velocity, RVO2 helps an agent find the velocity closest to the preferred velocity that will enable it to avoid collisions with all other agents. This is done by determining for each neighboring dynamic and static obstacle an *Optimal Reciprocal Collision Avoidance line (ORCA line)* . Each ORCA line determines the half plane in the velocity plane where the agent's velocity should lie to ensure that no collision occurs with that particular obstacle for the next τ seconds. τ is a parameter that specifies the number of seconds for which the chosen velocity should avoid a collision. From the set of half planes thus obtained, the optimal collision-avoiding velocity can be determined as the velocity within the permissible region for all the half planes that is closest to the preferred velocity. This can be determined efficiently using linear programming. Besides the speed and efficiency of the algorithm, another strong appeal of this model is that we need only set one parameter τ. For the experiments in this paper we use two values of τ; 0.5 seconds or 10 simulation time steps for avoiding dynamic agents and 0.05 seconds or 1 simulation time step for avoiding static obstacles. The value of τ translates in practical terms to how early a walker tries to avoid a collision with an obstacle.

7.2 Methodology

In this section we explain the simulations that were carried out and the analysis done. Java 6 and the MASON simulation framework [139] were used for creating and running the simulations. The simulated scenario consists of agents evacuating from a simple rectangular room with a single exit. The dimensions of the room are shown in Fig. 7.2. Evacuation of the room was simulated with $N = 50$, 100, 150, 200, 300, 500 and 1000 agents whose locations were randomly distributed within the room. For each N, we ran 100 simulations for each model, and the positions and velocities of all agents at all time steps were collected. For meaningful comparison between the three models, we assumed that each agent is a perfect circle with radius $R = 15$ cm [26], that has a preferred speed of 1.3 ms^{-1}, and a maximum speed of 2.6 ms^{-1} [**?**]. For the social force model we also assumed that all agents have the same mass of 60 kg.

Where possible, we have used the same settings for all three models to ensure a fair comparison. The values used for the remaining parameters required for the models was given in Sec. 7.1 along with the respective models. However, to the best of our knowledge, only the social force model has been calibrated against real world data [**?**]. The other two models are not calibrated beyond choosing a reasonable and believable model and the values chosen are taken such that they produce empirically believable results.

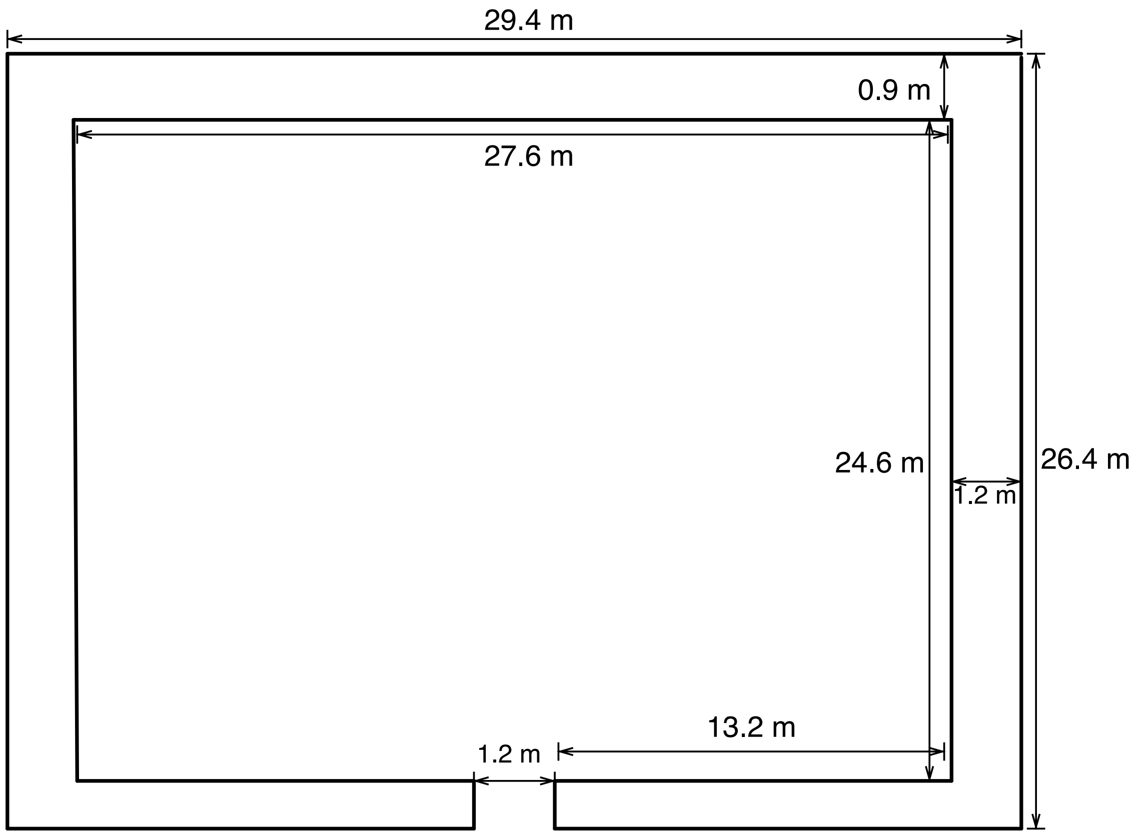


Figure 7.2: The environment setup used for the simulations in this paper.

7.2.1 Measurements

Depending on the context and motivation of the model there are several metrics that are generally used. For CA models that are generally used for studying macroscopic patterns, it is common to measure macro variables like the mean evacuation time [?] and flow rate [?]. For models like social force where the motivation is to study interactions at a more granular level, it is common to make empirical and qualitative observations like the lane effect [?]. Sometimes quantitative metrics like density-dependence of the flow or velocity are also measured [?]. From a graphics perspective, where performance is key, computation time [131], frame rate and run time per frame are generally measured against the number of walkers [133].

In this paper, we performed two main classes of measurements: time-based and distance-based measurements. For time-based measurements, we first measured the evacuation time distributions for different number of agents. To better understand the stages in the evacuation, we also divide the room into six different zones (see Fig. 7.3) to measure the evacuation time sub-distribution. The outer radii of Zones 1, 2, 3, 4, 5 and 6 are 5 m, 10 m, 15 m, 20 m, 25 m and 30 m respectively. We also measure the flow rate at the exit as a function of time for each model.

For distance-based measurements, we traced the trajectories of all agents to obtain the distribution of total distance travelled going from the initial position to the exit. Here, the total distance travelled D_i by agent i is just the sum of its displacements $\sum_{t=0}^{T_i} ||\vec{r}_i(t+1) - \vec{r}_i(t)||$, where T_i is the evacuated time of agent i. We also divide the room into 100×100 cells, and count the number of agents passing through each cell as the simulation progresses. This is then visualized as a heat map. Finally, we measure the ratio of the total distance travelled D_i by agent i to the minimum distance D_{min} it would cover if it evacuated along a straight line (For lattice model, D_{min} is the Manhattan distance between initial position of agent and exit). This in some sense quantifies the 'inconvenience', I_i experienced by the agent i during the evacuation.

$$I_i = \frac{D_i}{D_{\mathrm{min}}} \tag{7.7}$$

7.2.2 DISTATIS

After making six different measurements on three models, we discovered that when we look at the flow rates, the lattice gas model is more similar to the RVO2 model. However, if we look at the total distance travelled, the social force model is more similar to the RVO2 model. If we look at the zoned evacuation times, we find that the three models have very different distributions (see Sec. 7.3.1). Since we do not know *a priori* which measurements best discriminate the three models (or for that matter, best discriminate models from the real world), we want to be able to compare the three models quantitatively, incorporating information from all six measurements.

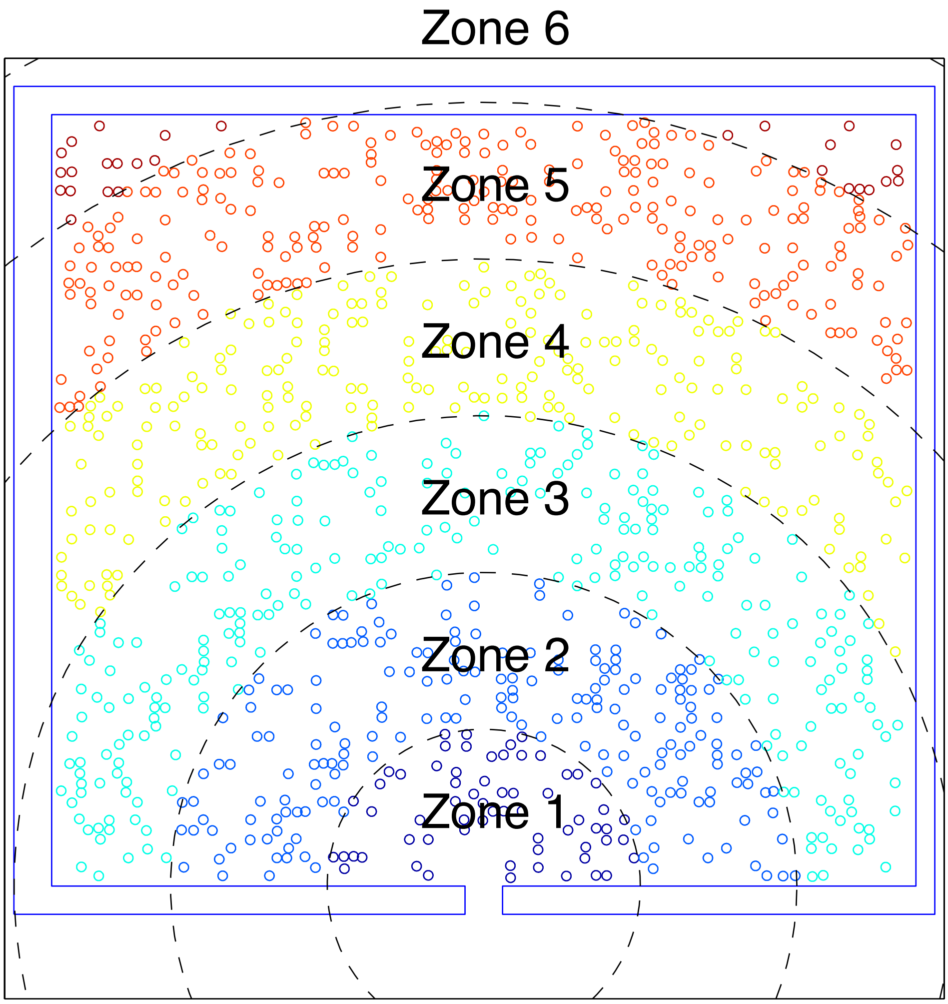


Figure 7.3: In our simulations, agents are grouped into six zones based on their initial distances from the exit. The outer radii of Zones 1, 2, 3, 4, 5 and 6 are 5 m, 10 m, 15 m, 20 m, 25 m and 30 m respectively.

To do so, we compute the *Jensen-Shannon divergence* [?]

$$D_{JS}[f_{k\mu}, f_{k\nu}] = H[f_k] - \frac{1}{2}H[f_{k\mu}] - \frac{1}{2}H[f_{k\nu}] \geq 0 \tag{7.8}$$

between the distributions $f_{k\mu}(z)$ and $f_{k\nu}(z)$ for measurement k of models μ and ν. Here, z is a continuous variable like evacuation time, distance travelled, or inconvenience,

$$H[f] = -\int dz\, f(z) \ln f(z) \tag{7.9}$$

is the *Shannon information function*, and

$$f_k(z) = \frac{1}{2}\left[f_{k\mu}(z) + f_{k\nu}(z)\right]. \tag{7.10}$$

If $f_{k\mu}(z)$ and $f_{k\nu}(z)$ are highly similar, we will get $D_{JS}[f_{k\mu}, f_{k\nu}] \approx 0$, whereas if $f_{k\mu}(z)$ and $f_{k\nu}(z)$ are very different, $D_{JS}[f_{k\mu}, f_{k\nu}] \gg 0$, i.e. the Jensen-Shannon divergence qualifies as a distance metric. In this way, we obtain six 3×3 distance matrices $\vec{D}_k$.

Then, we use the *DISTATIS* method [?] for analyzing multiple distance matrices. This is a generalization of the method of principal component analysis (PCA). STATIS is an acronym for the French expression 'Structuration des Tableaux à Trois Indices de la Statistique', which roughly means 'structuring three way statistical tables'. The difference between a straightforward application of the PCA method and the DISTATIS method is shown in Fig. 7.4. Instead of six different PCAs for the distance matrices obtained from the six different variables measured, and inevitably end up with conflicting conclusions on which models are more similar, we standardize the six distance matrices, and ask which variables are more similar to each other.

The idea behind DISTATIS is that the data points are similarly clustered in two variables, if their standardized distance matrices in these two variables are similar to each other. Therefore, if we compute the cross correlations between variables, we will discover which variables give more similar outcomes to which other variables through a PCA. Components of the first eigenvector obtained from this PCA tells us how important each variable is. By weighting the distance matrices of each variable by its component in the first eigenvector, we construct a *compromise matrix* whose matrix elements give us the most reliable similarity/dissimilarity between data points. A final PCA of this compromise matrix then gives the most reliable groups of data points. In Fig. 7.12, we show the six independent PCA results superimposed on the PCA of the compromise matrix.

7.3 Results and Discussion

The six measurements on the simulations are the (1) evacuation time, (2) zoned evacuation time, (3) passage density map, (4) total distance traveled, (5) inconvenience and (6) flow rate.

Here we show the results for (1) evacuation time (Fig. 7.5) and (2) zoned evacuation time (Fig. 7.6), (3) passage density map (Fig. 7.7), (4) total distance traveled (Fig. 7.8), (5) inconvenience (Fig. 7.9) and finally flow rate (Fig. 7.10) for all three models, with different number of agents.

7.3.1 Evacuation time

As Fig. 7.5 shows, the evacuation time distributions for all models have a uniform sub-distribution in the middle of the evacuation, which signals congestion at the exit, once we have $N > 50$ agents. However, in the RVO2 model this uniform sub-distribution is flanked by two small peaks. These two small peaks suggest a higher evacuation rate *just before* congestion sets in and *just before* congestion dissipates in the RVO2 model. This is not observed in real crowds, and hence is clearly an artifact of the model.

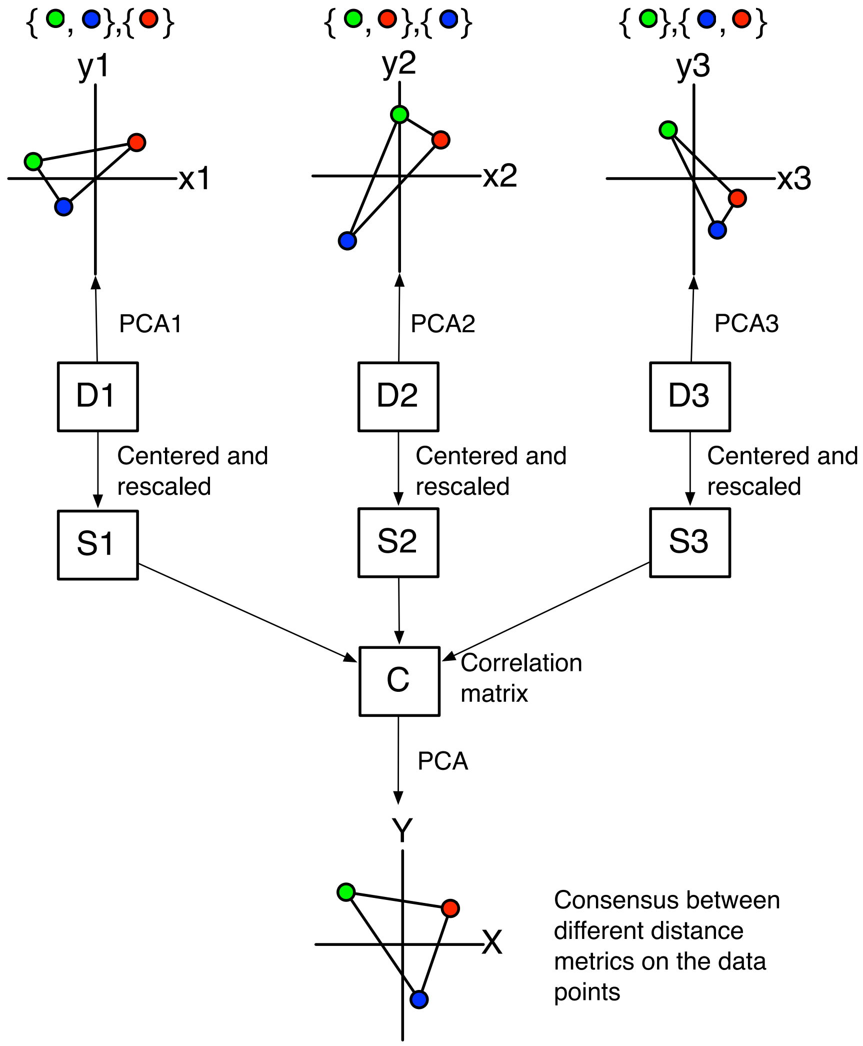


Figure 7.4: In many classification problems, we can define different distance metrics for the same set of data points to measure how dissimilar they are to each other. In this figure we show three different distance matrices D1, D2, and D3. If we perform principal component analysis (PCA) on them separately (PCA1, PCA2, PCA3), we are not likely to agree on which data points are more similar to each other. In the DISTATIS method, we first standardize the distance matrices by centering and rescaling, to get S1, S2, and S3. If two data points are indeed more similar to each other than they are with the third, then we expect this similarity structure to be reflected in S1, S2, and S3, i.e. two standardized distance matrices would have very similar patterns of matrix elements. With this in mind, we reshape the matrices S1, S2, and S3 to make them into vectors of distances. We then compute the cross correlations between these vectors, before performing PCA on the correlation matrix C. This PCA tells us which distance matrices agree with each other more, and which less. The result is a consensus between different distance metrics, based on which a single PCA will discover the similarity structure between the data points.

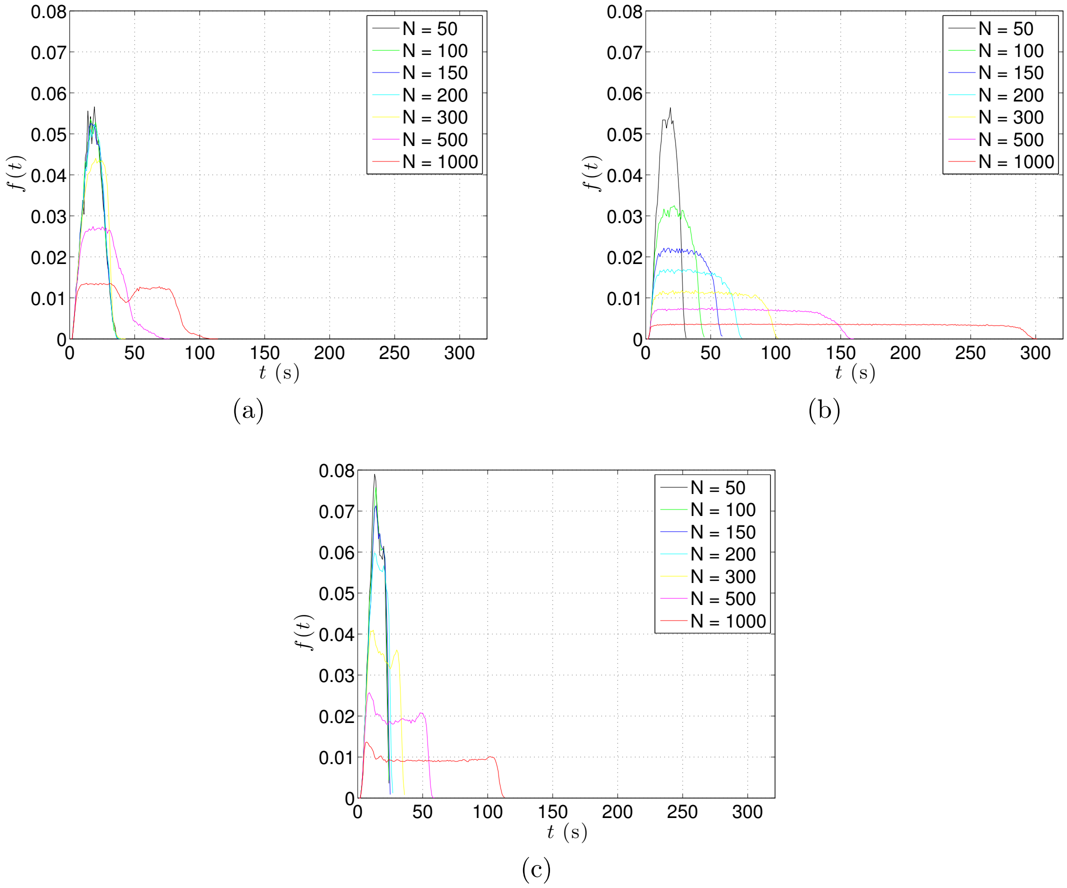


Figure 7.5: Evacuation time distributions for the (a) lattice gas, (b) social force, and (c) RVO2 models for $N = 50, 100, 150, 200, 300, 500, 1000$ agents. For each model and N, the distribution is built from 100 simulations.

Comparing the three models, we find that the social force model has the longest evacuation times of up to five minutes. More importantly, careful inspection reveals fluid-like crowd dynamics around the exit in the RVO2 and lattice gas models. These can be seen in our videos `http://www.youtube.com/watch?v=P64p3nlH_P4` and `http://www.youtube.com/watch?v=vJONzi5Bykw`. In the RVO2 model, an obvious back flow can also be seen during the sudden gush of agents toward the exit. Due to the strong repulsion forces, we see a solid-like behavior in the social force model when the exit becomes congested (see our video `http://www.youtube.com/watch?v=3Ot7m959_yo`).

In addition, we divided the room into six zones, as shown in Fig. 7.3, based on the distance to the exit, to determine how strongly the crowds mix in the three models. The distributions of zoned evacuation times are shown in Fig. 7.6. These tell us that mixing is strong in the lattice gas and RVO2 models, but weak in the social force model. This mixing dynamics can be seen more clearly from our videos `http://www.youtube.com/watch?v=qeoJotgEUxk` (lattice gas), `http://www.youtube.com/watch?v=uZpd5LODYZs` (RVO2), and `http://www.youtube.com/watch?v=wEB6Ya0o_yw` (social force).

From the movies of the lattice gas and RVO2 simulations, we see that agents from the nearer zones get pushed to the side once there is congestion at the exit. In these two models, agents prefer to keep moving when it is possible for them to do so. Agents in the social force model behave differently: once the exit becomes congested, they will become nearly stationary and wait for their turn to go through the exit.

7.3.2 Passage density

The passage density heat map of agent locations averaged over 100 simulations provides information about the spatial-temporal trace of agents during their evacuation. This is crucial when analyzing the spatial structure of congestions. In Fig. 7.7a, we see a channel leading straight through the exit. This channel acts as an attractor, because once an agent gets onto this, it will be forced statistically towards the exit ($P_{t,y} = 1.00$). Though not as pronounced as for the lattice gas model, two left-right symmetric channels also formed in the RVO2 model (Fig. 7.7c). These two channels point roughly from the centers of mass of the left and right halves of the room towards the exit. No such artificial channels can be seen in the passage density map of the social force model (Fig. 7.7b).

Comparing the three models, we also see that the RVO2 model (Fig. 7.7c) has the most compact passage density, whereas the social force model (Fig. 7.7b) has the least compact passage density. In particular, in the region just in front of the exit, the RVO2 model gives rise to very high passage density. This high passage density cannot be attributed to agents stepping over a cell once or twice, as in the lattice gas

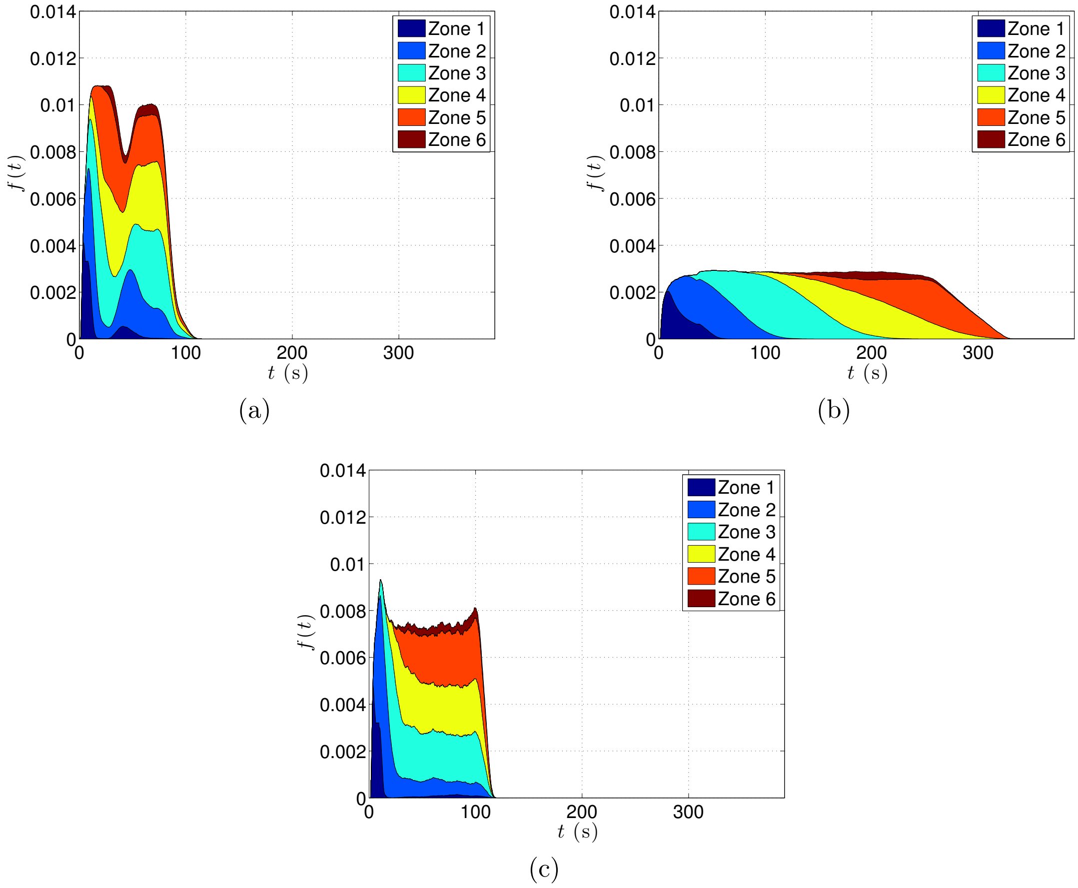


Figure 7.6: Zoned evacuation time distributions for the (a) lattice gas, (b) social force, and (c) RVO2 models for $N = 1000$ agents in six zones, with zone 1 closest to the exit and zone 6 furthest away (see Figure 7.3). For each model, the distribution is averaged over 100 simulations.

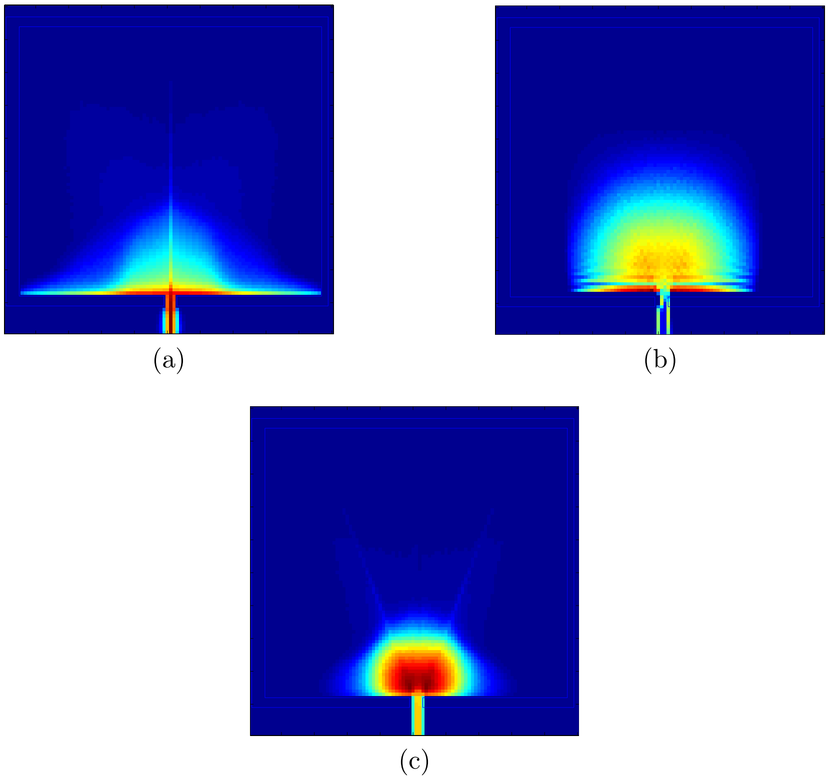


Figure 7.7: Passage density maps of $N = 1000$ agents averaged over 100 simulations for the (a) lattice gas, (b) social force, and (c) RVO2 models. In these color maps, the exit is located at the bottom.

and social force models. In the RVO2 model, this high passage density is produced by repeated visits to the same cell by individual agents that are always moving.

7.3.3 Total distance traveled distribution and inconvenience

To measure the difficulty (inconvenience) for an agent to squeeze through the crowd during evacuation, we measured the *total distance traveled* and as well as the *inconvenience* (defined in Eq. 7.7). As we can see in Fig. 7.8b and Fig. 7.8c, the distributions of total distance traveled are very similar for the social force and RVO2 models. The lattice gas model, on the other hand, has very different distributions of total distance traveled (Fig. 7.8a). This is because space is continuous in the two former models, but discrete in the lattice gas model.

However, when we compare the distributions of inconveniences in Fig. 7.9, we find the lattice gas model is more qualitatively similar to the RVO2 model, though the typical inconveniences in the lattice gas model are larger than the those in the RVO2 model. For different N, the distribution peaks around the same inconvenience for both models. In contrast, the peak position of the inconvenience distribution of the social force model depends strongly on the number of agents in the simulation.

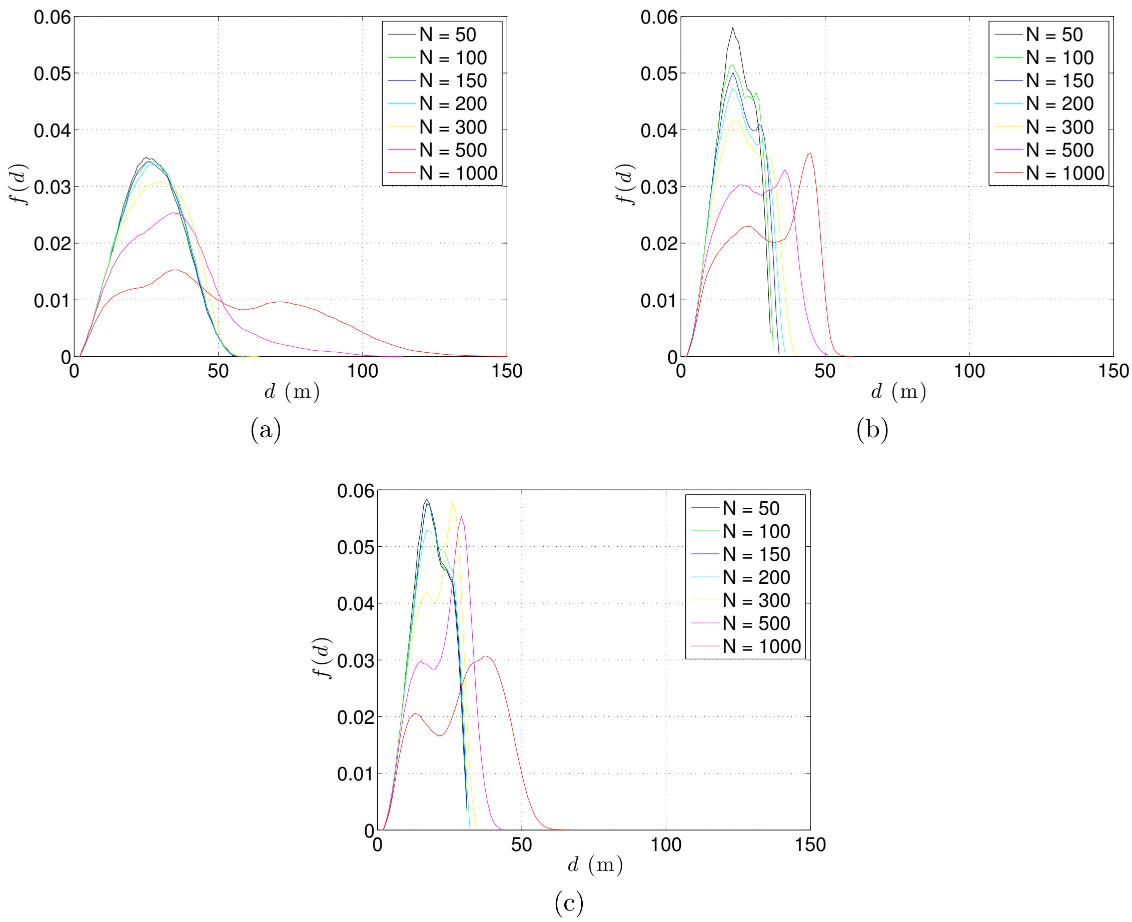


Figure 7.8: Distributions of total distance traveled for the (a) lattice gas, (b) social force, and (c) RVO2 models. For each model and N, the distribution is averaged over 100 simulations.

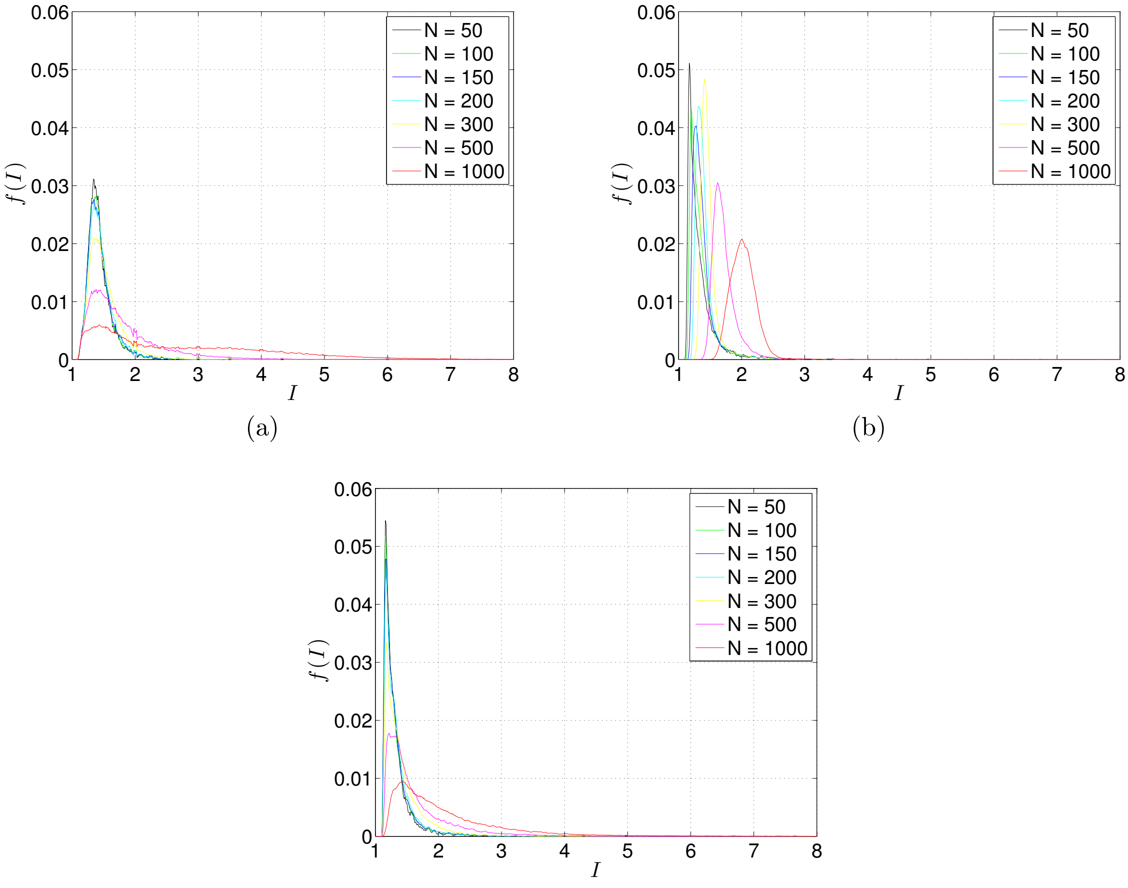


Figure 7.9: Distributions of inconveniences for the (a) lattice gas, (b) social force, and (c) RVO2 models. For each model and N, the distribution is averaged over 100 simulations.

7.3.4 Evacuation rate

We also measured the flow rate of agents at the exit. As shown in Fig. 7.10a, the flow rate of the lattice gas model saturates at around 11.8 persons per second due to the finite sizes of the agents and the exit. The social force model has the lowest flow rate of 2.2 people per second (Fig. 7.10b), because agents slow down dramatically at the end as a result of strong repulsive forces between agents. From Fig. 7.10c), we see the same peaks before and after the congestion period for the RVO2 model, a consequence of the liquid-like dynamics of RVO2 crowds.

In an attempt to compare simulation results with real data we obtained a number of videos showing real-life evacuations [**?** **?**] during the Sichuan Earthquake on May 12, 2008. We analysed two such videos, `http://www.youtube.com/watch?v=-y38ebiAnQw` and `http://www.youtube.com/watch?v=e1yapP3z_L4`. Because the geometry of the scene and the viewing angles are not known, we could only measure the flow rates on a second-by-second basis from these two videos (Fig. 7.11), for comparison against what we measured in our simulations. Unlike the computational study, where we could average over 100 simulations to get smoothly varying flow rates, the flow rates measured from the videos are noisy. However, sensible comparisons can still be made. In `http://www.youtube.com/watch?v=-y38ebiAnQw`, the crowd is shown to evacuate through the check-out counters of a Walmart supermarket. The flow rate was high, but there was no congestion, because of the wide exit. This flow rate cannot be compared against our simulations of evacuation through a narrow exit.

In `http://www.youtube.com/watch?v=e1yapP3z_L4`, students were evacuating their classroom through a narrow door. From the video, we see that the width of the door allows no more than three school children to exit simultaneously. Therefore, the exit dimensions seem to correspond to the exit dimensions use in our simulations. From Fig. 7.11, we see that the average flow rate in the congestion phase is about 3 persons per second. This is far below the congestion flow rate in the lattice gas model, and very close to the congestion flow rate of the social force model. Based on this observable, we find that the social force model agrees best with the real data. This small test also tells us that the three models can be distinguished through their congestion flow rates, if other observables could not be measured.

7.3.5 DISTATIS comparison

Finally, we make use of the DISTATIS method explained in Sec. 7.2.2 to compare the three models with all six different measurements. Fig. 7.12 shows the different measurements of the three models projected onto their first two principal components. The barycenters for the three models are also shown. From Fig. 7.12 we see that based on the total distance traveled (green), the social force and RVO2 models have similar distributions, which are both very different from that of the lattice gas model. On

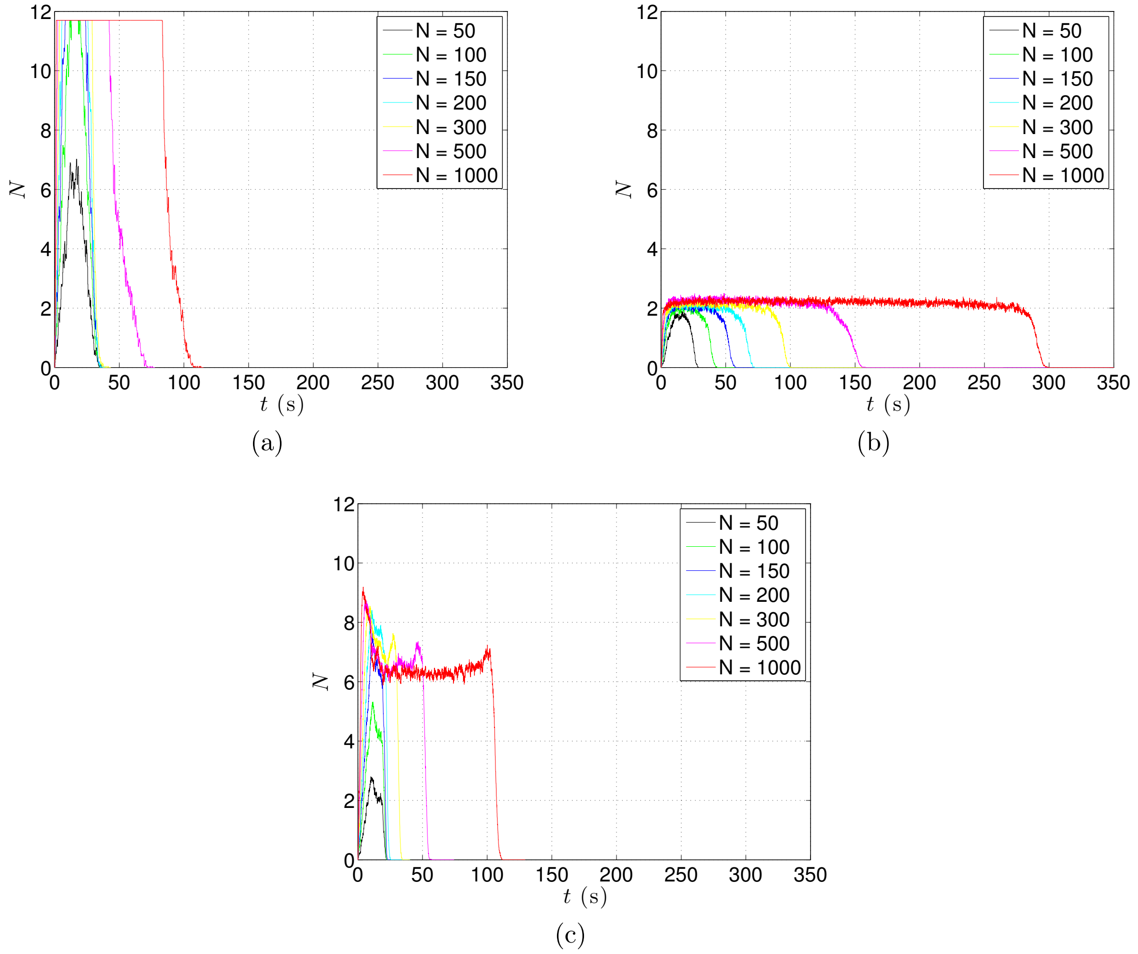


Figure 7.10: Flow rates at the exit as functions of time for the (a) lattice gas, (b) social force, and (c) RVO2 models. For each model and N, the flow rate is averaged over 100 simulations.

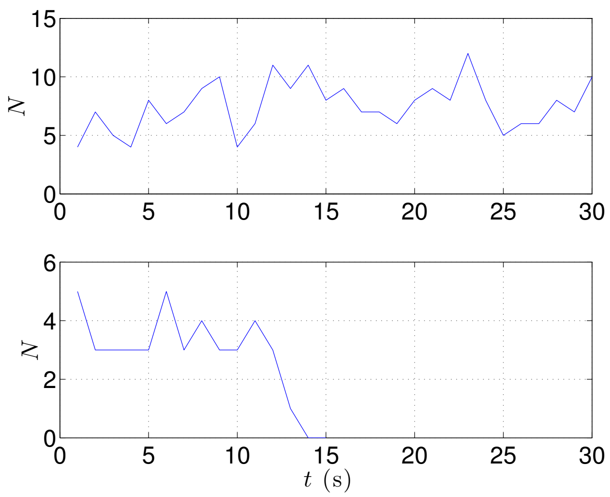


Figure 7.11: The flow rates for evacuation during the May 2008 Sichuan Earthquake: (top) through the check-out counters of a Walmart supermarket in Chengdu, China (`http://www.youtube.com/watch?v=-y38ebiAnQw`); and (bottom) through the narrow exit of a classroom in an elementary school in Sichuan, China (`http://www.youtube.com/watch?v=e1yapP3z_L4`).

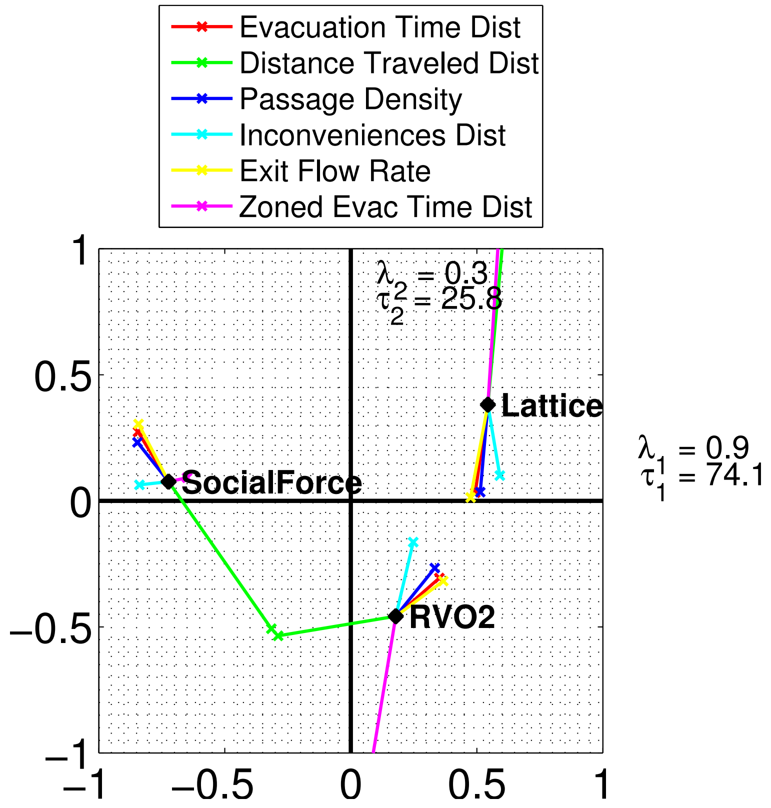


Figure 7.12: The DISTATIS analysis of the three models with $N = 1000$ agents. In this plot, τ is the quality of compromise, and λ is the eigenvalue.

the other hand, the lattice gas and RVO2 models have similar distributions that are significantly different that of the social force model.

More importantly, we find the clustering of some observables: evacuation time, passage density, and flow rate all tells us that the lattice gas model is similar to the RVO2 model, and different from the social force model. We also find the inconvenience and zoned evacuation time provide some indication that the three models are qualitatively different. In fact, the DISTATIS method indicates that the zoned evacuation time is one key metric that clearly distinguishes the three models. Therefore, any real world experiments should attempt to measure this. This observable maximally discriminates between the three models and therefore it is reasonable to expect it will also discriminate between real-world data and the models.

7.4 Conclusion

To conclude, we simulated emergency evacuation from a rectangular room with a single narrow exit using three models: (1) lattice gas, (2) social force, and (3) RVO2, with different starting number of agents in the room. From these simulations, we measured six observables: (1) evacuation time, (2) zoned evacuation time, (3) passage density, (4) total distance traveled, (5) inconvenience and (6) flow rate. Besides qualitative comparison of the various distributions obtained, we also compared the three models quantitatively using the DISTATIS method. Comparing the evacuation time, passage density, and flow rate distributions, we find that the lattice gas and RVO2 models are similar, both of which are very different from the social force model. On the other hand, if we compare the distribution of total distance traveled, the social force and RVO2 models are more similar to each other, and very different from the lattice gas model. We compared the simulated congestion flow rates of the three models to congestion flow rates of school children evacuating from their classroom during the May 2008 Sichuan Earthquake, and find based on this observable that the social force model agrees best with the egress data. Finally, from an analysis of the DISTATIS we have identified the zoned evacuation time as the one observable metric that can best discriminate between these models, and also between models and real-world data

Chapter 8

Conclusion and Future Work

The previous chapters have introduced the IBEVAC architectures and it's constituent models. Only the IBP module has been implemented so far. The preliminary design of the remaining modules was discussed in Chapter ??. However, design work still needs to be done before the model design can be finalized. In Sect. 8.2.1, an expected time frame for finalizing the design details of the model is first discussed. Following this, in Sect. 8.2.2, some of the implementation details and tools used are discussed along with an estimated schedule for completion of implementation of the model. Finally, some of the work involved in validation of the model is then presented in Sect. 8.2.3. However, before the future work and plan of action is discussed, Sect. 8.1 first summarizes and concludes the report.

8.1 Summary and Conclusion

In the beginning of this report, the idea of crowd egress simulation and the importance of modeling accurately the entire process of evacuation right from the pre-evacuation behavior to the time where all the evacuees have evacuated the building was introduced. Then a brief overview of the limitations of existing models. The information based approach to modeling crowd egress that is presented in this report was intorduced next.

Chapter 2 gave a comprehensive overview of the literature. The multidisciplinary nature of the problem was presented next; this was followed by a detailed discussion of the current state of our knowledge of human behavior process in fire evacuations. The various crowd behavior theories developed over the years was introduced and an analysis of the similarities and differences of these models was presented. This was followed by an overview of the different approaches to the problem of computationally modeling and studying a crowd evacuation. This was followed by a detailed analysis of some notable models and the strengths and weaknesses of these models.

Chapter 3 introduced a complete information based model of an agent complete with an information based perception system, a communication engine, a memory system, a decision making engine and a navigation system.

A basic Information Based Perception (IBP) model has already been developed and it was presented in Chapter 4. The chapter also presented some simulation results that illustrated the effects of using an Information Based Perception on motion planning. In Chapter **??**, the other modules in the model were presented along with some of the related work and basic details of each module.

Finally, this chapter presented a breakdown of the future work that remains along with an estimated time frame for completion of each of these tasks. These are illustrated in Fig. 8.2.

8.2 Future Work

This section discusses the work that remains to be done for the completion of this thesis. As mentioned above, this section is subdivided into three sections highlighting the work remaining in model design, implementation and validation. A Gantt chart figuratively illustrating the schedule proposed in this section is shown in Fig. 8.2 at the end of this chapter.

8.2.1 Model design

The development and implementation of any simulation model generally begins with an extensive study of the literature, followed by an identification of shortcomings in existing work and establishment of a problem to be solved. The next step is to conceptually develop a model that can in principle tackle the identified problem. This is where the process of *model design* starts. In Sect. 3.1 of this report, the problem of accurately modeling accurately the behavior of humans in a crowd simulation was broken down into six constituent building blocks. By doing this, an overall architecture that could solve the problem at hand was developed. However, at this point, much work still remained in designing each of the remaining modules. For each module, the same process has to be repeated, i.e. existing work should be studied, the strengths and shortcomings of existing models, if any, should be analyzed and a design of each model along with its structure and working should be developed. During this process care should be taken to ensure that each module not only fulfills its own task but it should also work well with the remaining modules and help towards achieving the model's objective. Depending on some factors like the existing work and the modeler's experience, the design of a model can take a few days or weeks. The preliminary background studies and design work has been done for all the modules and these were discussed over the previous chapters. In the following paragraphs, the work that remains in the design of each module of the IBEVAC architecture is presented along with an estimated time to completion for those modules whose design has not been finalized.

Of the seven modules in the IBEVAC architecture, the IBP module's design has been more or less completed and it was presented in detail in Chapter 4 along with details of its implementation and some experiments conducted. However, as stated earlier in this report, minor work still remains in updating this perception module to obtain cue information from the environment and in detailing an approach to implementing a dynamic information limit. By a conservative estimate, 10 days would suffice to complete this work.

The proposed 4-level Navigation Module is currently being designed and implemented as an extension to the navigation system used in DEPATHSS egress simulation system. DEPATHSS will be discussed in more detail in Sect. 8.2.2 along with other implementation details. For now, it is sufficient to note that the Navigation Module's design has been completed.

The background details and proposed details of the Event Knowledge Module was discussed in much detail in Sect. **??**. The proposed model is coherent and its working and interaction with the other modules has been satisfactorily developed. While it has not been implemented and tested yet, from the perspective of model design it is reasonable to assume that the work has been fully completed.

Even though, the agent description module's working has been discussed in Sect. **??** details regarding its interaction with the other modules hasn't been finalized. This cannot be finalized until the other models have been finalized. However, being a small module, this work should take just about 2 days.

Section **??** discussed some of the most prominent work that's been done in modeling cognitive maps in robotics and simulation systems. However, a more thorough study of existing knowledge of cognitive maps and testing and validation of the proposed Environment Knowledge Module is required before the design can be finalized. The designing of the model should involve about 25 days work.

The Communication Module (Sect. **??**) is in a similar state to the Environment Knowledge Module, not least because its working is highly dependent on the latter's structure and working. A similar estimate of 15 days work to be done concurrently with the environment knowledge module is made.

The basic details of the working of the Planning Module was presented in Sect. **??**. While this is coherent and its interaction with the other modules are relatively clear, the actual strategies to be implemented and the constituent tasks have not been developed. The relevant literature about normal tasks that are carried out by individuations has been analyzed and presented in Sect. 2.2. However, some tasks are highly context dependent and cannot be finalized until the exact details of the scenario are finalized. This work can take up to 25 days.

Table 8.1: Time-frame for tasks in Model Design

Task	Percentage Work Completed	Estimated Time to Completion
Overall Architecture	100%	-
IBP Module	90%	10 days
Navigation Module	100%	-
Event Knowledge Module	100%	-
Environment Knowledge Module	60%	25 days
Agent Description Module	70%	2 days
Communication Module	60%	15 days
Planning Module	70%	25 days
Total	93%	51 days

8.2.2 Implementation and simulation

The *implementation* of a model refers to the process of converting the conceptual design into code, i.e. a computational model. The section presents some of the details of the implementation like the tools used and the existing work on which the model is built. Section 8.2.2.3 then presents an estimated time-frame for completion of different implementation related tasks.

8.2.2.1 The MASON framework

The IBEVAC model is implemented in Java using the MASON framework [139]. MASON consists of a discrete event simulation core and visualization library that can be used for agent based simulations with a large number of agents. The framework provides features to allow modelers to run multiple replications and create checkpoints from which simulations can be restarted easily. The ease of implementation of inspectors to study particular agents or other aspects of the model and integration with java media framework library (for videos and snapshots), jGraph and java3D make MASON especially appealing for the purpose of this simulation. The framework internally adopts the model-view-controller pattern and completely decouples the view from the controller and the model and makes it easy for a modeler to adopt the same approach. This is critical for studying simulations because a visualization need only be used when particular parts of the simulation need to be observed and analyzed and at all other times more simulations can be run without the additional computational burden of visualization.

8.2.2.2 DEPATHSS

DEPATHSS is a simulation system for symbiotic simulations of evacuation scenarios (Screenshot in Fig. 8.1). It is not directly related to the IBEVAC model. However, the Java based implementation of the simulation system provided a good starting point for

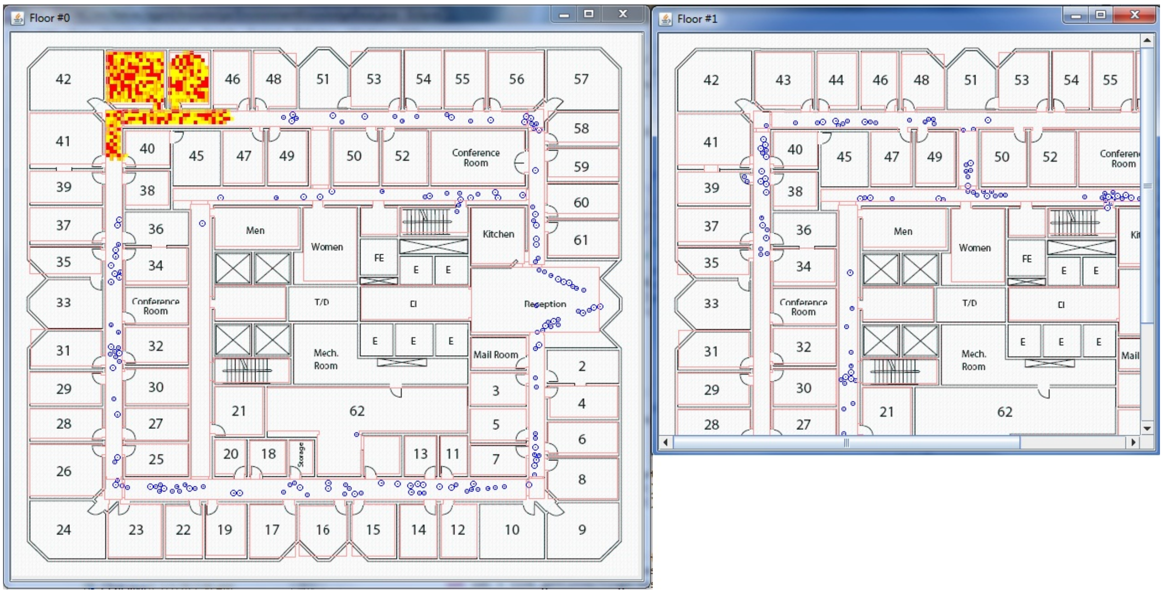


Figure 8.1: This figure shows a screenshot of the evacuation simulation using DEPATHSS of a 2-floor office building with fire propogation modelled (The red, yellow and orange color at the top left of the screen on the first floor). Agents are in blue.

implementation of the IBEVAC model and helps remove a lot of programming work that might have been required if the model had to be implemented from scratch.

A Finite Difference Model based implementation of fire propagation used in DEPATHSS is adapted to the MASON framework to simulate fire and smoke propagation in IBEVAC. The smoke will be given a higher diffusion rate so that it spreads at a faster rate.

Another very useful feature of the DEPATHSS system is the ability to create and store layouts of buildings in a generic XML format that can be easily imported into the model. This will be invaluable during experimentation and validation.

As mentioned earlier, the DEPATHSS system's navigation system is being extended to use the 4-level navigation architecture mentioned in this paper. This navigation system can also be integrated into the IBEVAC architecture without much difficulty.

Like the navigation system DEPATHSS is also currently being extended with simple personal cognitive maps for agents and knowledge transfer between agents. This can initially be used in IBEVAC while developing the other modules. Once the other modules have been developed the Communication and Environment Knowledge Modules can be modeled as required by replacing the existing system.

All this implies that, most of the lower level tasks like the framework, basic goal directed navigation and fire and smoke simulation have been completed and tested and most of the work remains only in implementing a higher level behavioral model which is the key contribution of this thesis. An estimate of the time frame required for different aspects of this implementation is considered next.

Table 8.2: Time frame for tasks in Model Implementation

Task	Estimated Time to Completion
Preliminary Model	16 days
IBP Module Integration	15 days
Event Knowledge Module	35 days
Planner	45 days
Agent Description Module	5 days
Environment Knowledge	20 days
Communication Module	20 days
Total	12 weeks

8.2.2.3 Time frame for model implementation

Even though, the aforementioned DEPATHSS system has been developed in Java it is not integrated with the MASON framework whose features and strengths mentioned in Sect. 8.2.2.1 would be extremely useful. Besides this, some work has to be done in integrating the features of DEPATHSS into an IBEVAC like architecture. Thus the first objective in implementing the model would be to create a simple simulation system where a group of agents simply move towards the exit of a building. This preliminary system will not be implementing any higher level behavior. This process can take up to 16 days.

The next step in implementation would involve integrating the Information Based Perception system into this simulation system. While the IBP module has been implemented and tested, this implementation and testing were done in a different much simpler framework. However, the implementation was in Java and using Mason, so 15 days would be sufficient to complete the implementation of the IBP module.

As mentioned in the previous section, there already exists a simple version of the Environment Knowledge Module and the Communication Module. Thus the development of the more complicated IBEVAC version of these modules with notions of trust and forgetfulness can be put on hold till after the Planning Module and Event Knowledge Module have been developed. The Planning Module will have to be initially implemented with some simple strategies because it is essential to the working of the Event Knowledge Module. In fact, both these modules will have to be developed in parallel because they are highly interconnected in their working. This process will also involve upgrading the IBP module to perceive cues from the environment. This would be the most substantial work involved in the implementation of the model. We estimate that this can take about 50 days.

Next the Agent Description Module can be developed. While this module itself is not that complicated; implementing this module will result in changes in the Event Knowledge Module and the strategies in the Planner. This will take about a week to implement.

Finally, the Communication and Environment Knowledge Module will have to be modified and changed to work as specified in the IBEVAC model. This will take about 20 days to implement.

8.2.3 Validation

Validation for crowd simulation is a very difficult problem for which there isn't any accepted solution. Especially in the present case of a system that models and simulates a fire evacuation, it is ethically and practically impossible to actually start a fire and observe the evacuees.

In general, macroscopic models like the lattice gas models validate their model by simulating the evacuation from a room and constructing a graph of the rate of evacuation against time [?]. This method might ensure accurate macro level behavior but gives no guarantee of the micro level accuracy or behavior of the model. This is of little use to civil defense or fire authorities trying to figure out a way to limit the damage caused by fires.

Pelechano [?] and the Gamma group at University of North Carolina [83, 97, 140] use the presence or absence of certain characteristics of motion like *reciprocal dances* [97, 140] and continuity of the movement [?] to measure the realism of the movement. A somewhat related method is one that uses visual validation. In this approach, videos or actual crowds are observed and certain patterns are observed; The model is validated by checking its ability to produce similar patterns and behavior.

Comparing against videos of crowds moving is a reliable method for validation. But according to Banerjee et al. [141], what is missing is a clear and reliable method for ensuring that the validation is accurate. To counter this problem, they have suggested a system for quantitative validating agent based crowd simulation systems. They use a novel, automated method for comparing the results (the movements) produced by the simulation against videos of crowds evacuating from a stadium that are available from CCTVs. They call this method quantitative validation. The area in the simulation is first divided into regions. The movement produced in each of these regions is compared against the movement in the video. A similar method is also used in other studies [142, 143]. They have verified the working of this automated method by validating a model of evacuation from a stadium. This method of quantitative validation is unlikely to be useful in a fire evacuation simulation because it is difficult, if not impossible, to get videos of crowds taking part in an actual fire evacuation.

The best records of peoples actions during fires and evacuations is available through interviews of the evacuees. Various studies [9, 12, 37, 42] give a very accurate account of people's behaviors during fires. Models of fire evacuation can start of by trying to produce the sorts of actions that were revealed in these interviews. This brings us to the concept of micro validation. In this method, rather than trying to produce the complete, detailed real life situation "as is" in a computer simulation, we try to produce and verify certain actions and behaviors that were characteristic of the evacuation. Realistically speaking, this is all that can be expected from the system, because it is impossible to predict the movement of every person in an evacuation without at least having a complete and comprehensive personal history of the person. This is not *that* severe a limitation because it still gives a fairly good idea of the crowd's reaction.

Data plays an important part in validating these multi agent systems. The more data, the better a system can be validated. But as the scale of the system and its complexity of the system increases, interviews and surveys become progressively less useful. Another method for validating agent based systems, especially human behavior is by using the power of human computation [144].

In [**?**], we suggested a methodology that used key ideas from human computation as a means of collecting large amounts of contextual behavioral data. They key principle of this approach is to design games such that they act as a means of framing behavioral questions to try and capture people's natural and instinctive decisions. This method has the key advantage of being able to generate large sets of data from a large sample set. The approach also offers the advantages outlined by Sterman [145], in that using carefully designed scenarios and games provides a more contextual and interactive form for phrasing a question.

In the context of validation, it might be interesting and relevant to mention the work we are currently doing in comparing the results produced by social forces [136] and RVO2 [83] against a simple lattice gas model [**?**] when simulating simple situation like exit from a room or merging of two paths.

A combination of the different approaches for validation that are available will be used to validate the IBEVAC model. Validation is a continuous process that begins right from the point of development of the model. The validation period consists of planning and running experiments on the simulation, gathering data and debugging the model.

8.2.3.1 Validation

To determine an estimated time frame for the validation process, it is helpful to divide this process of validation into four phases.

Firstly, existing work on validation will have to be studied in detail to understand the pros and cons of different approaches to validation. While some of the work has been done in this regard, three to four weeks will have to be spent in consolidating this knowledge of existing validation methodologies.

Table 8.3: Breakdown of tasks in Validation

Task	Estimated Time to Completion
Phase 1: Literature Review	30 days
Phase 2: Planning	90 days
Phase 3: Experimentation	100 days
Phase 4: Analysis	100 days
Total	17 weeks

Next, based on this literature and the module being validated, different experiments and will have to be designed for verifying and validating the working and effect of each module on the agent's behavior. These experiments can be in the form of scenarios to be run on the simulation or actual real world experiments or experiments conducted on the aforementioned use of human computation [?]. This process will take a considerable amount of planning. However, the major portion of this work will be done alongside the third phase of the validation process which involves conducting these planned experiments and gathering data. However, the process of running simulation experiments and collecting data can be automated to an extent through scripts. This enables more work on phase 2 and 4 to be done while the data is being generated. A period of 115 days is allotted for completing phases 2 and 3 of validation.

The fourth and final phase of validation involves aggregating the collected data and analyzing it. At this point changes might have to be made in the model and further experiments might have to be planned and implemented. A period of 100 days is alloted to this phase. It is important to note the unlike the development and implementation tasks, validation tasks are generally more open ended (except for phase 1). Hence work on validation is likely to continue till very near the date of thesis submission.

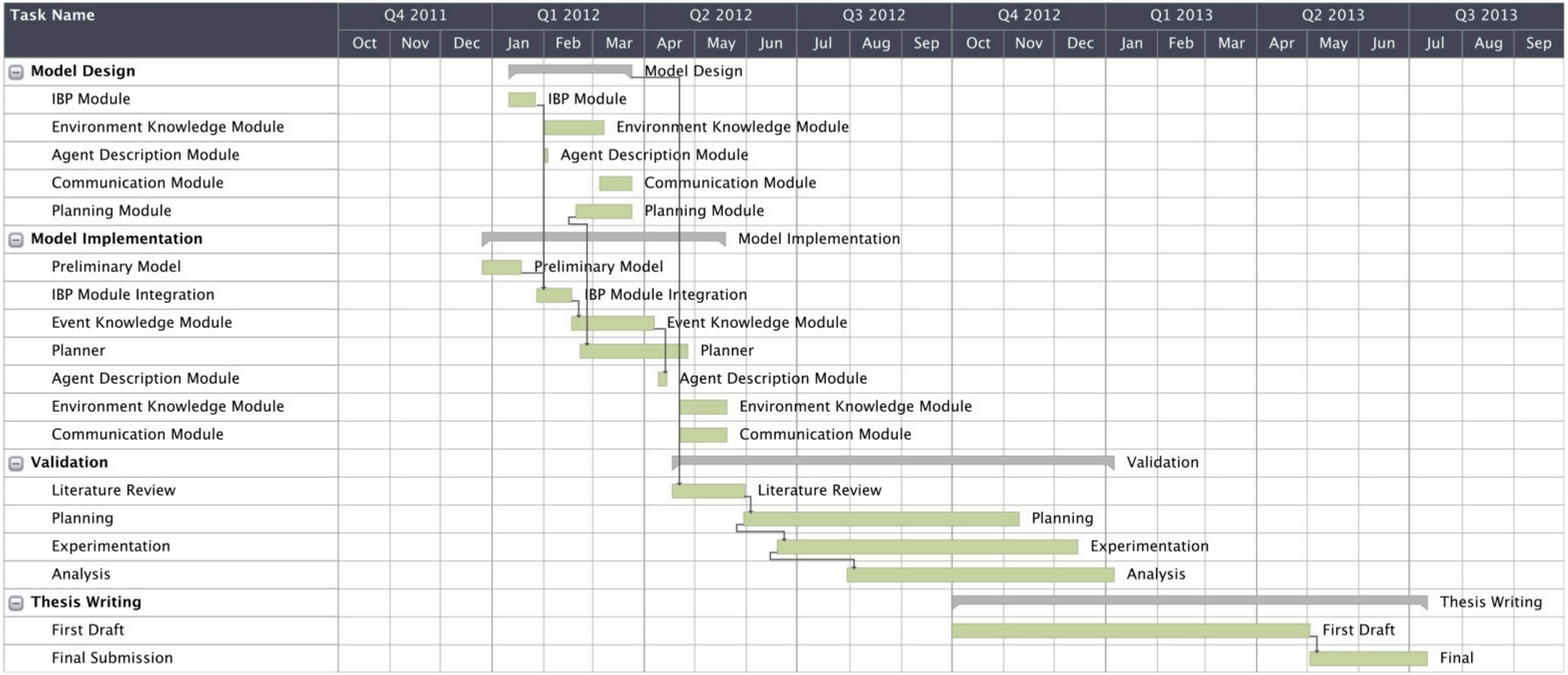


Figure 8.2: Gantt Chart showing the plan of action for the present thesis. The chart excludes weekends, public holidays and 21 days a year from the calender to account for allowed leave.

Appendix A

Model Class Structure

Figure A.1 shows the overall class structure of the model. As can be seen in the diagram, the visualization of the model (IBEVACGui Class) is decoupled from the model itself (IBEVACModel). This allows the modeler to run batches of simulations faster and without interruption. The IBEVACModel class contains the scheduler that runs the simulation and it also holds an instance of the Simulation Space. To effectively consider and model each different part of the model, the Space class delegates most of its functions to the classes within it. Of this, the fireSpace uses the scheduler to simulate the spreading of the fire and stores in the form of a field that can be used by the Portrayal Instance in the visualization class to render the fire. The Physical Environment and the level 0 motion classes are used to ensure the consistency of the environment. The remaining class is the space in which the agents and obstacles are stored. This space also stores information on the relationships between areas, floors and links. Again, delegation is used to maximize modularity and minimize the dependencies between the different classes.

The Agent class in the Fig. A.1 is shown in more detail in Fig. A.2. This is the entity that implements the behavior of the agent. Classes like the Agent Portrayal and Agent Inspector are responsible for displaying the agent and displaying and editing values of a particular agent. The IbevacAgent delegates these tasks to these classes. The IBEVAC architecture explained in Chapter 3 is modeled almost exactly as suggested by the architecture and the class diagram illustrates this clearly.

The agent's perception is modeled as an interface so that the perception system can easily be extended and improved at a later date without affecting the rest of the model. During each step of the model, the agent's perception is first updated. This perception updates the environment and event knowledge base of the agent. Changes in the environment and event knowledge can trigger a plan change in the planner. Depending on the current state and activity being completed by the agent, the planner passes a goal point to the navigation module which generates the velocity and movement of the agent in each time step.

One of the key novelties of the IBEVAC model is in the way that cues are modeled. Different kinds of cues are generated by the environment and the agents. Each cue implements the Cue interface. Each agent can sense these Cue type objects from the environment and react to them.

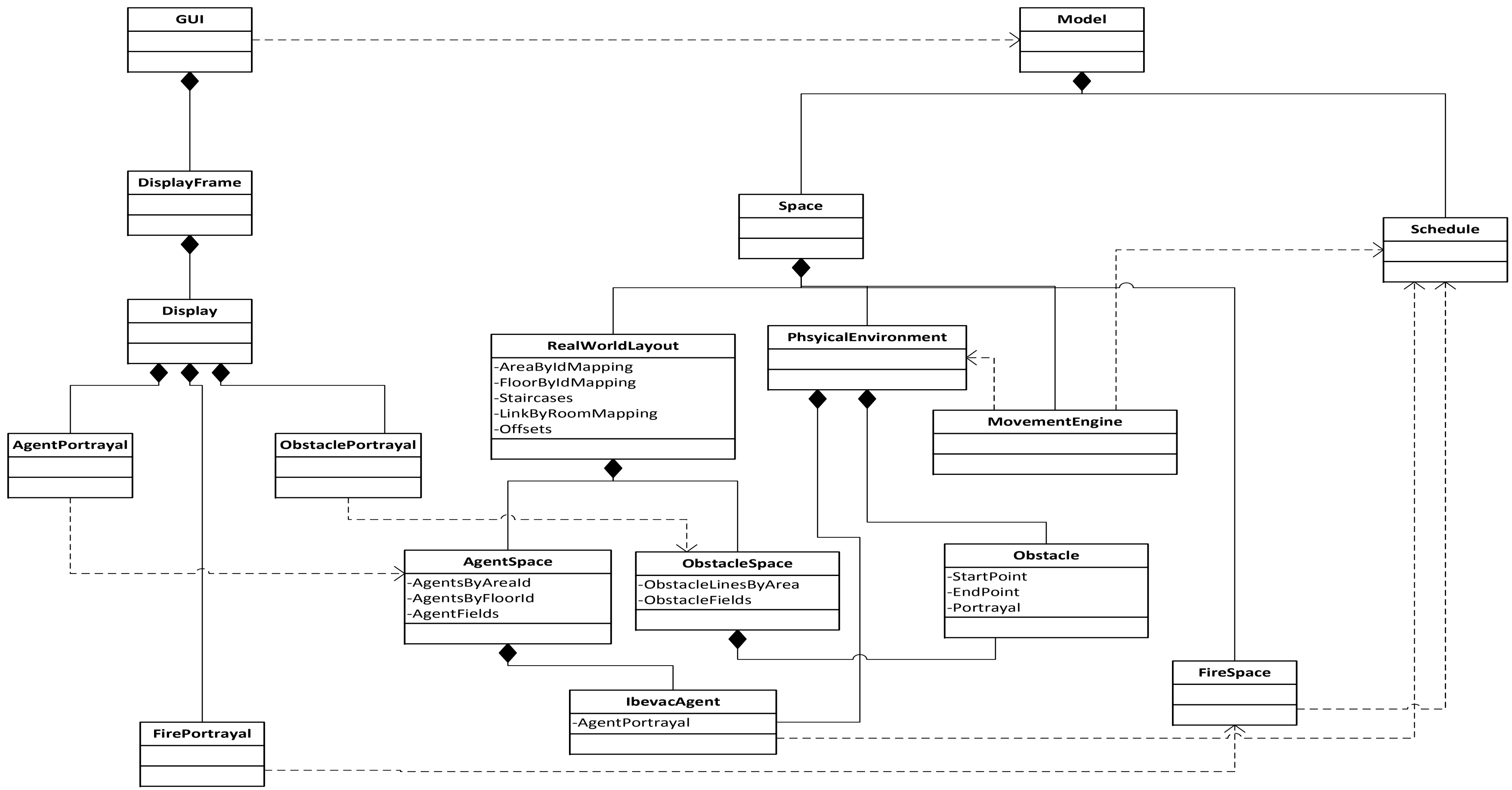


Figure A.1: Class Diagram shows the overall class structure of the model

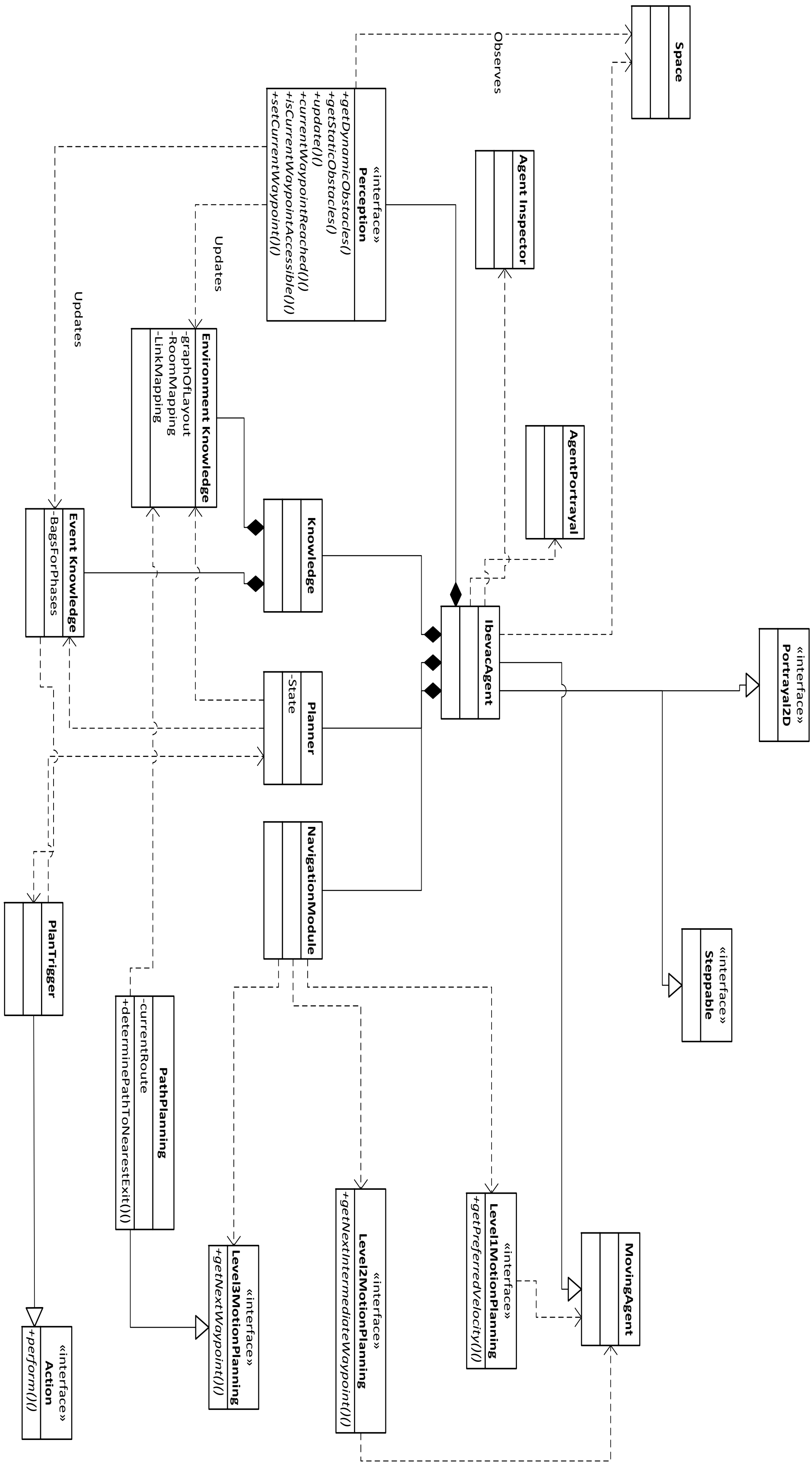


Figure A.2: This Class Diagram shows the agent class in detail

Appendix B

Validity check for Markov analysis

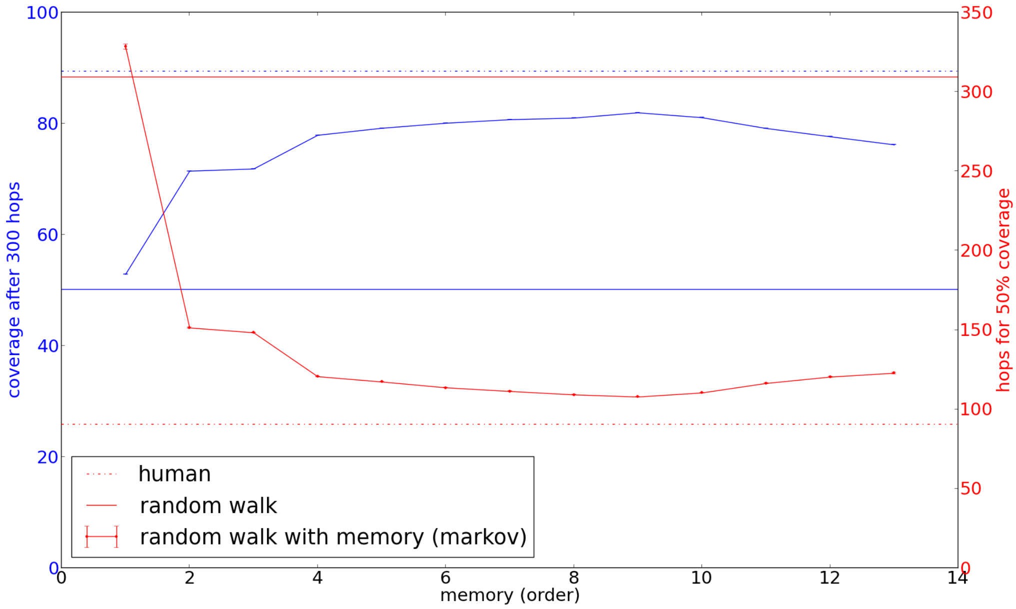
B.1 Effect of dataset size

To check this, we hypothesized that if the peak does not change on doubling the dataset size then the pattern that is seen is not an artifact of the dataset size. We plotted the same graph for N=22 and N=44 and checked if there is a shift in the peak to a higher value. As shown in Figure B.1 there is clearly no shift. The peak value still remains at 7-8 and starts dropping at 9.

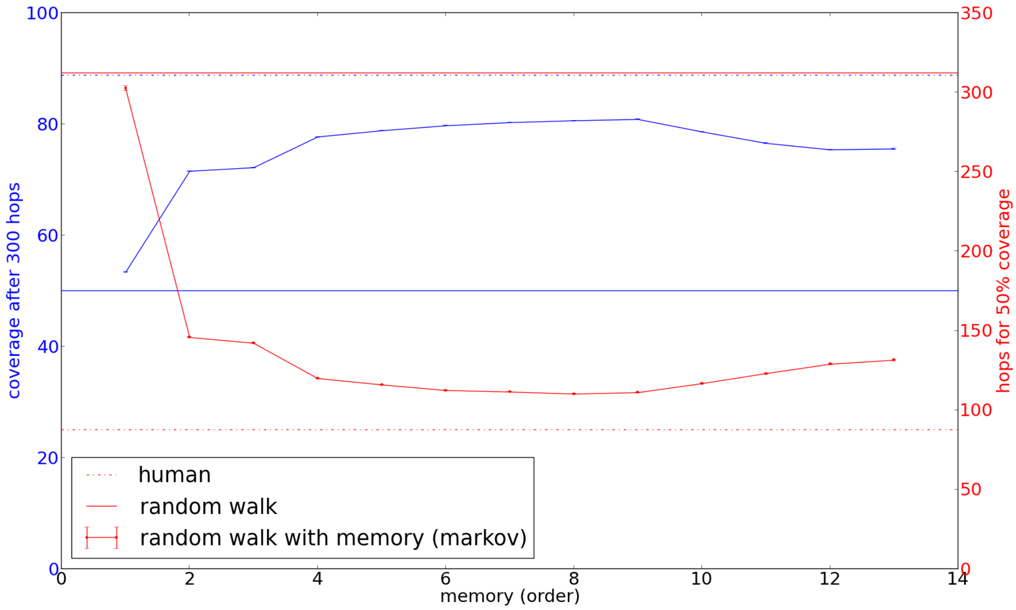
B.2 Decision base size at decision points

Since the markov-data calculation is based on aggregating the actions of the agents at each decision point, the quality of the calculation is based on the amount of data available to make predictions. We refer to this as the *decision base size* of the calculations.

For each node in each path generated the number of people that have actually made a decision at that point is calculated. We divide each of these values by the number of decisions that are possible at that point. So a single decimal value is obtained for each node of each path generated. The average of this over all nodes of a 300 hop path gives the *path specific decision base.* 30,000 paths are generated the average of these path specific decision bases gives an estimate of the decision base that is used, and in effect the reliability of the calculations in the preceding sections.



(a) Hop and coverage for 44 players



(b) Hop and coverage for 22 players

Figure B.1: Hop and coverage graphs different size of datasets. Seems to indicate that the peak is not dependent on data size

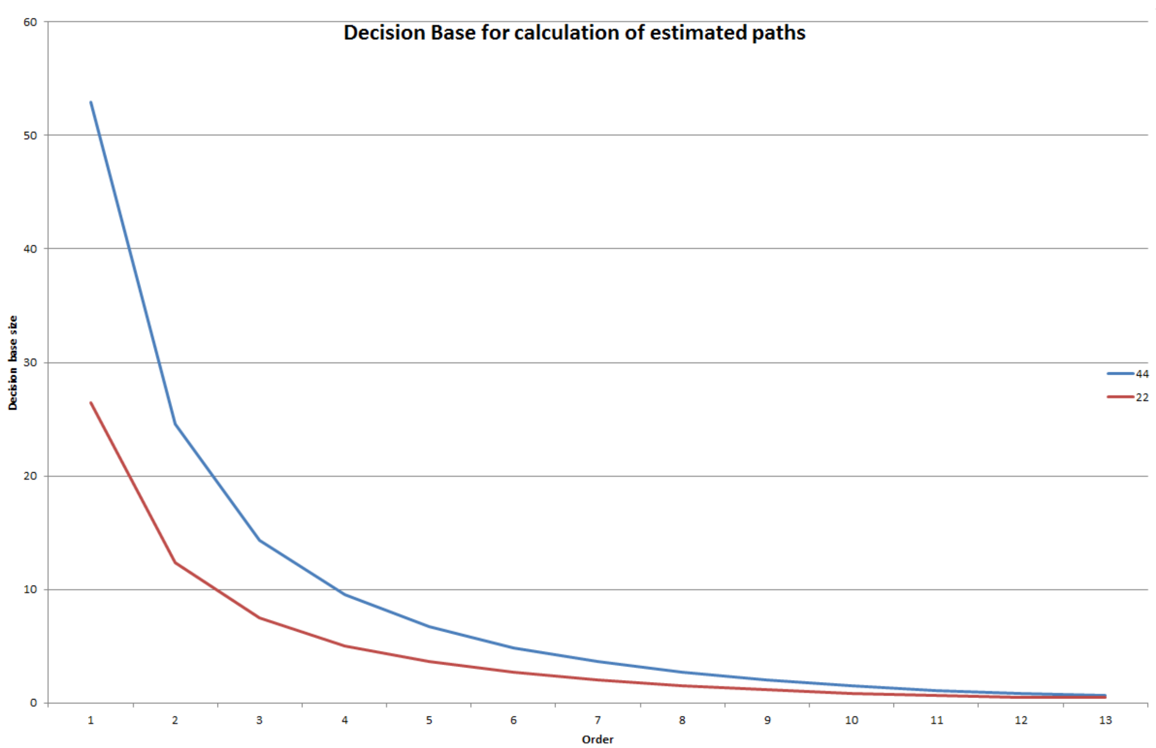


Figure B.2: Comparison of the decision bases

References

[1] B. Arthur. (2010, Dec.) Complexity Economics 2.

[2] G. K. Still, "Crowd Dynamics," Ph.D. dissertation, University of Warwick, University of Warwick, Department of Mathematics, Aug. 2000.

[3] S. Regelous and K. Mannion. (2011) Massive Software – Simulating Life.

[4] C. W. Reynolds, "Flocks, herds and schools: A distributed behavioral model," *Computer Graphics*, vol. 21, no. 4, pp. 25–34, Jul. 1987.

[5] V. Viswanathan and M. Lees, "Modeling and Analyzing the Human Cognitive Limits for Perception in Crowd Simulation," in *Transactions on Computational Science*, M. L. Gavrilova, K. C. Tan, and C.-V. Phan, Eds. Springer, pp. 1–20.

[6] S. J. Guy, J. Chhugani, S. Curtis, P. Dubey, M. C. Lin, and D. Manocha, "PLEdestrians: a least-effort approach to crowd simulation," in *SCA '10: Proceedings of the 2010 ACM SIGGRAPH/Eurographics Symposium on Computer Animation*, University of North Carolina. Eurographics Association, Jul. 2010.

[7] H. L. Klüpfel, M. Schreckenberg, and T. Meyer-König, "Models for crowd Movement and egress Simulation," *Traffic and Granular Flow*, 2005.

[8] B. E. Aguirre and G. Santos, "A Critical Review of Emergency Evacuation Simulation Models," in *Building Occupant Movement During Fire Emergencies*. Gaithersburg, Maryland: University of Delaware, 2004, pp. 1–54.

[9] M. R. Torres, "Every Man for Himself? Testing Multiple Conceptual Approaches of Emergency Egress on Building Evacuation During a Fire," Ph.D. dissertation, University of Delaware, University of Delaware, Apr. 2010.

[10] J. D. Sime, "Crowd psychology and engineering* 1," *Safety Science*, vol. 21, pp. 1–14, 1995.

[11] G. A. Miller, "The magical number seven, plus or minus two: some limits on our capacity for processing information." *Psychological review*, 1956.

[12] M. Kobes, I. Helsloot, B. de Vries, and J. G. Post, "Building safety and human behaviour in fire A literature review," *Fire Safety Journal*, vol. 45, no. 1, pp. 1–11, Dec. 2009.

[13] A. Schadschneider, W. W. F. Klingsch, H. Kluepfel, T. Kretz, C. Rogsch, and A. Seyfried, "Evacuation Dynamics: Empirical Results, Modeling and Applications," *Physical Review E*, vol. physics.soc-ph, Feb. 2008.

[14] S. Reicher, "The Psychology of Crowd Dynamics," in *Blackwell Handbook of Social Psychology: Group Processes*, M. A. Hogg and R. S. Tinsdale, Eds. Blackwell Publishers Ltd, Jan. 2008, pp. 182–208.

[15] R. L. Paulsen, "Human behavior and fires: An introduction," *Fire Technology*, vol. 20, pp. 15–27, May 1984.

[16] J. D. Sime, "Affiliative Behavior During Escape to Building Exits," *Journal of environmental psychology*, vol. 3, pp. 21–41, 1983.

[17] F. Ozel, "Time Pressure and Stress as a Factor During Emergency Egress," *Safety Science*, vol. 38, pp. 95–107, 2001.

[18] T. T. Pires, "An approach for modeling human cognitive behavior in evacuation models," *Fire Safety Journal*, vol. 40, no. 2, pp. 177–189, Mar. 2005.

[19] F. A. Aveni, "The Not-So-Lonely Crowd: Friendship Groups in Collective Behavior," *Sociometry*, vol. 40, no. 1, pp. 96–99, Mar. 1997.

[20] P. M. A. Sloot, A. Schoneveld, and J. De Ronde, "Large-scale simulations of complex systems, part I: conceptual framework," *Working Papers*, 1997.

[21] E. D. Kuligowski, "The Process of Human Behavior in Fire," National Institute of Standards and Technological, Tech. Rep. 1632, May 2009.

[22] K. Andrée and B. Eriksson, "Cultural differences in an evacuation scenario," Ph.D. dissertation, Lund University, Lund, 2008.

[23] A. Sandberg, *Unannounced evacuation of large retail stores*, ser. An evaluation of human behaviour and the computer model SIMULEX, R. Jonsson and T. J. Shields, Eds. Lund Institute of Technology, Lund University: Lund University, Oct. 1997.

[24] N. Pelechano, K. O'Brien, B. Silvermann, and N. L. Badler, "Crowd Simulation Incorporating Agent Psychological Models, Roles and Communication," in *International Workshop on Crowd Simulation*. University of Pennsylvania, 2005, pp. 21–30.

[25] H. Aydt, M. Lees, L. Luo, W. Cai, M. Y. H. Low, and S. K. Kadirvelen, "A Computational Model of Emotions for Agent-Based Crowds in Serious Games," in *Intelligent Agent Technologies.* Lyon, France: School of Computer Engineering, Nanyang Technological University, 2011, pp. 1–9.

[26] X. Pan, "Computational Modeling of Human and Social Behaviors For Emergency Egress Analysis," Ph.D. dissertation, Stanford University, The Department of Civil and Environmental Engineering, Stanford University, Jun. 2006.

[27] R. d. S. França, M. d. G. B. Marietto, and M. B. Steinberger, "A Multi-agent Model for Panic Behavior in Crowds," in *Fourteenth Portuguese Conference on Artificial Intelligence.* Federal University of ABC, Santo André, Säo Paulo, Brazil, Oct. 2009, pp. 463–472.

[28] C. Cocking and J. Drury, "DON'T PANIC! Altruistic behaviour in crowd emergencies," in *Altruism Conference*, Oct. 2005, pp. 1–11.

[29] G. Proulx, "Occupant behaviour and evacuation," in *9th International Fire Protection Symposium.* Munich: Institute for Research in Construction, National Research Council Canada, May 2001, pp. 219–232.

[30] G. Ramachandran, "Human behavior in firesa review of research in the United Kingdom," *Fire Technology*, pp. 149–155, May 1990.

[31] A. Mawson, "Understanding mass panic and other collective responses to threat and disaster," *Psychiatry: Interpersonal and Biological Processes*, pp. 95–113, 2005.

[32] G. Proulx, "Playing with fire understanding human behavior in burning buildings," *ASHRAE Journal*, vol. 45, no. 7, pp. 33–35, Jul. 2003.

[33] D. Tong and D. Canter, "The Decision to Evacuate a Study of the Motivations which Contribute to Evacuation in the Event of Fire Theoretical deficiencies," *Fire Safety Journal*, vol. 9, pp. 1–9, 1985.

[34] D. Berry and R. Hanley. (2000, Jan.) Questions About Fire Safety After Deaths at Seton Hall .

[35] T. L. Graham and D. J. Roberts, "Qualitative overview of some important factors affecting the egress of people in hotel fires," *International Journal of Hospitality Management*, vol. 19, pp. 79–87, Feb. 2000.

[36] G. Proulx, "Evacuation Time and Movement in Apartment Buildings," *Fire Safety Journal 24*, vol. 24, pp. 229–246, 1995.

[37] D. A. Purser, "Quantification of behaviour for engineering design standards and escape time calculations," *Safety Science*, vol. 38, pp. 157–182, 2001.

[38] G. Proulx, "High-rise office egress the human factors," in *Symposium on High-Rise Buidling Egress*. New York City: Institute of Research in Construction, National Research Council, Canada, May 2007, pp. 1–6.

[39] C. Cocking and J. Drury, "The Mass Psychology of Disasters and Emergency Evacuations: a Research Report and Implications for the Fire and Rescue Service," *Fire Safety : Technology and Management*, vol. 10, pp. 13–19, 2008.

[40] E. Quarantelli, "The Nature and Conditions of Panic," *American Journal of Sociology*, vol. 60, no. 3, pp. 267–275, Nov. 1954.

[41] J. Drury, C. Cocking, S. Reicher, A. Burton, D. Schofield, A. Hardwick, D. Graham, and P. A. Langston, "Cooperation Versus Competition in a Mass Emergency Evacuation: a New Laboratory Simulation and a New Theoretical Model," *Behavior Research Methods*, vol. 41, no. 3, pp. 957–970, Aug. 2009.

[42] C. Cocking, J. Drury, and S. Reicher, "The Psychology of Crowd Behavior in Emergency Evacuations: Results From Two Interview Studies and Implications for the Fire & Rescue Service," *The Irish Journal of Psychology*, vol. 30, pp. 1–31, 2007.

[43] B. Cornwell, "Bonded Fatalities: Relational and Ecological Dimensions of a Fire Evacuation," *The Sociologial Quarterly*, vol. 44, no. 4, pp. 617–638, Oct. 2003.

[44] J. Chertkoff, R. Kushigian, and M. A. McCool Jr, "Interdependent exiting: The effects of group size, time limit, and gender on the coordination of exiting," *Journal of environmental psychology*, vol. 16, pp. 109–121, 1996.

[45] B. D. Jones, "Bounded Rationality," *Annual Review of Political Science*, vol. 2, pp. 297–321, 1999.

[46] R. L. Davis, B. A. Therrien, and B. T. West, "Working memory, cues, and wayfinding in older women," *Journal of Applied Gerontology*, vol. 28, no. 6, pp. 743–767, 2009. [Online]. Available: http://jag.sagepub.com/content/28/6/743.abstract

[47] R. Fahy and G. Proulx, "Toward Creating a Database on Delay Times to Start Evacuation and Walking Speeds for Use in Evacuation Modeling," in *2nd International Symposium on Human Behavior in Fire*. Boston, MA, USA: National Research Council Canada, 2010, pp. 175–183.

[48] M. J. Kinsey, E. R. Galea, P. J. Lawrence, D. Blackshields, L. Hulse, R. Dat, and G. Sharp, "Modelling pedestrian escalator behaviour," *Pedestrian and Evacuation Dynamics 2008*, Dec. 2009.

[49] S. M. Olenick and D. J. Carpenter, "An Updated International Survey of Computer Models for Fire and Smoke," *Journal of Fire Protextion Engineering*, vol. 17, pp. 87–110, May 2003.

[50] P. A. Langston, R. Masling, and B. N. Asmar, "Crowd dynamics discrete element multi-circle model," *Safety Science*, vol. 44, no. 5, pp. 395–417, Jun. 2006.

[51] P. A. Thompson and E. W. March, "A computer model for the evacuation of large building populations," *Fire Safety Journal*, vol. 24, pp. 131–148, 1995.

[52] M. Isobe, D. Helbing, and T. Nagatani, "Many-particle simulation of the evacuation process from a room without visibility," *Physical Review E*, vol. cond-mat.stat-mech, Jun. 2003.

[53] J. M. Watts Jr, "Computer models for evacuation analysis," *Fire Safety Journal*, vol. 12, pp. 237–245, 1987.

[54] S. M. V. Gwynne, E. R. Galea, M. Owen, P. J. Lawrence, and L. Filippidas, "A Review of the Methodologies Used in the Computer Simulation of Evacuation From the Built Environment," *Building and Environment*, vol. 34, no. 6, pp. 741–749, Nov. 1999.

[55] E. D. Kuligowski, "4.4 Review of 28 Egress Models," in *Workshop on Building Occupant Movement During Fire Emergencies*, 2005.

[56] X. Zheng, T. Zhong, and M. Liu, "Modeling crowd evacuation of a building based on seven methodological approaches," *Building and Environment*, vol. 44, no. 3, pp. 437–445, Mar. 2009.

[57] T. M. Kisko and R. L. Francis, "Evacnet+: a computer program to determine optimal building evacuation plans," *Fire Safety Journal*, vol. 9, no. 2, pp. 211–220, 1985.

[58] G. Lämmel, M. Rieser, and K. Nagel, "Large Scale Microscopic Evacuation Simulation," *Pedestrian and Evacuation Dynamics 2008*, no. Chapter 48, pp. 547–553, Dec. 2009.

[59] M. Bierlaire, G. Antonini, and M. Weber, "Behavioral dynamics for pedestrians," in *International Conference on Travel Behavior Research*. Lucerne: EPFL, Aug. 2003.

[60] P. Lino, G. Maione, and B. Maione, "Modeling and Simulation of Crowd Egress Dynamics in a Discrete Event Environment," in *2009 IEEE Multi-conference on Systems and Control*. Saint Petersburg, Russia: IEEE, Jul. 2009, pp. 843–848.

[61] L. Henderson, "On the fluid mechanics of human crowd motion," *Transportation research*, vol. 8, pp. 509–515, 1974.

[62] B. Banerjee, A. Abukmail, and L. Kraemer, "Advancing the Layered Approach to Agent-based Crowd Simulation," in *22nd Workshop on Principles of Advanced and Distributed Simulation.* School of Computing, The University of Souther Mississippi, 2008, pp. 185–192.

[63] ——, "Layered Intelligence for Agent-based Crowd Simulation," *SIMULATION*, vol. 85, no. 10, pp. 621–633, Sep. 2009.

[64] S. Marconi, "Mesoscopical modelling of complex systems," Ph.D. dissertation, Université de Genève, Genève, 2002.

[65] C. M. Henein and T. White, *Crowds and Cellular Automata*, ser. Lecture Notes in Computer Science, D. Hutchison, T. Kanade, J. Kittler, J. M. Kleinberg, F. Mattern, J. C. Mitchell, M. Naor, O. Nierstrasz, C. Pandu Rangan, B. Steffen, M. Sudan, D. Terzopoulos, D. Tygar, M. Y. Vardi, G. Weikum, S. Yacoubi, B. Chopard, and S. Bandini, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2006, vol. 4173.

[66] S. Bandini, M. L. Federici, and G. Vizzari, "Situated Cellular Agents Approach to Crowd Modeling and Simulation," *Cybernetics and Systems*, vol. 38, no. 7, pp. 729–753, Aug. 2007.

[67] J. M. Epstein, "Agent-based computational models and generative social science," *Complexity*, vol. 4, no. 5, pp. 41–60, May 1999.

[68] E. Bonabeau, "Agent-based modeling methods and techniques for simulating human systems," in *Arthur M. Sackier Colloquium of the National Academy of Sciences.* Icosystem Corporation, 545 Concord Avenue, Cambridge, May 2002, pp. 7280–7287.

[69] X. Li, W. Mao, D. Zeng, and F.-Y. Wang, "Agent-based social simulation and modeling in social computing," in *Intelligence and Security Informatics 2008 Workshops.* Chinese Academy of Sciences, 2008, pp. 401–412.

[70] E.-W. Augustijn-Beckers, J. Flacke, and B. Retsios, "Investigating the Effect of Different Pre-Evacuation Behavior and Exit Choice Strategies Using Agent-Based Modeling," *Procedia Engineering*, vol. 3, pp. 23–35, 2010.

[71] D. Helbing and P. Molnar, "Social Force Model for Pedestrian Dynamics," *Physical Review E*, vol. cond-mat.stat-mech, pp. 4282–4286, May 1995.

[72] A. H. Maslow, "A theory of human motivation." *Psychological review*, vol. 50, pp. 370–396, 1943.

[73] A. Orton, G. L. Clore, and A. Collins, *The Cognitive Structure of Emotions.* University of Illinois at Urbana-Champaign: Cambridge University Press, 1990.

[74] M. Owen, E. R. Galea, and P. J. Lawrence, "The Exodus Evacuation Model Applied To Building Evacuation Scenarios," *Journal of Fire Protection Engineering*, vol. 8, no. 2, pp. 65–84, Jan. 1996.

[75] S. M. V. Gwynne, E. R. Galea, P. J. Lawrence, and L. Filippidas, "Modelling occupant interaction with fire conditions using the buildingEXODUS evacuation model," *Fire Safety Journal*, vol. 36, pp. 327–357, 2001.

[76] C. Hollmann, P. J. Lawrence, and E. R. Galea, "Introducing Emotion Modelling to Agent-Based Pedestrian Circulation Simulation," in *Pedestrian and Evacuation Dynamics 2010.* Maryland, USA: University of Greenwich, Mar. 2010, pp. 1–4.

[77] J. Tsai, N. Fridman, E. Bowring, and M. Brown, "ESCAPES-Evacuation Simulation with Children, Authorities, Parents, Emotions, and Social comparison," in *10th International Conference on Autonomous Agents and Multiagent Systems*, K. Turner, P. Yolum, L. Sonenberg, and P. Stone, Eds. Kagan Tumer, Pinar Yolum, Liz Sonenberg, and Peter Stone, May 2011.

[78] X. Pan, C. S. Han, K. Dauber, and K. H. Law, "A Multi-Agent Based Framework for the Simulation of Human and Social Behaviors During Emergency Evacuations," *AI & SOCIETY*, vol. 22, no. 2, pp. 113–132, Jun. 2007.

[79] S. Russel and P. Norvig, "Intelligent Agents," in *Artificial Intelligence: A Modern Approach.* Prentive-Hall, Inc., 1995, pp. 30–52.

[80] ——, "Informed Search and Exploration," in *Artificial Intelligence: A Modern Approach.* Prentice Hall, 1995, pp. 122–147.

[81] H. Nan, M. Lees, S. Zhou, and V. Viswanathan, "Pattern Based Motion For Crowd Simulation," *Transactions on Edutainment*, pp. 1–10, 2011.

[82] S. J. Guy, J. Chhugani, C. Kim, N. Satish, M. C. Lin, D. Manocha, and P. Dubey, "ClearPath: highly parallel collision avoidance for multi-agent simulation," in *SCA '09: Proceedings of the 2009 ACM SIGGRAPH/Eurographics Symposium on Computer Animation.* ACM Request Permissions, Aug. 2009.

[83] S. J. Guy, J. van den Berg, and M. C. Lin, "Geometric methods for multi-agent collision avoidance," in *Symposium on Computer Graphics*, University of North Carolina. Utah, USA: Proceedings of the 2010 annual symposium on Computational geometry, Jun. 2010, pp. 115–116.

[84] H. Yeh, S. Curtis, S. Patil, and J. van den Berg, "Composite agents," in *Symposium on Computer Animation.* University of North Carolina, 2008.

[85] J. Hochberg and E. McAlister, "A Quantitative Approach, to Figural "Goodness"," *Journal of Experimental Psychology*, vol. 46, no. 5, pp. 361–364, Nov. 1953.

[86] N. Cowan, "The Magical Number 4 in Short-Term Memory: a Reconsideration of Mental Storage Capacity," *Behavioral and Brain Sciences*, vol. 24, no. 01, pp. 87–114, Feb. 2001.

[87] L. Itti and C. Koch, "Computational modeling of visual attention," *Nature*, vol. 2, pp. 194–203, Mar. 2001.

[88] J. K. O'Regan, R. A. Rensink, and J. J. Clark, "Change-blindness as a result of 'mudsplashes'," *Nature*, vol. 398, p. 34, Mar. 1999.

[89] J. Triesch, D. H. Ballard, M. M. Hayhoe, and B. T. Sullivan, "What you see is what you need," *Journal of Vision*, vol. 3, pp. 1–9, Feb. 2003.

[90] D. E. Broadbent, "Applications of Information Theory and Decision Theory to Human Perception and Reaction," *Progress in Brain Research*, vol. 17, pp. 309–320, 1965.

[91] R. W. Hill Jr, "Modeling Perceptual Attention in Virtual Humans," in *Computer Generated Forces and Behavioral Representation*, Orlando, May 1999, pp. 1–11.

[92] N. Courty, E. Marchand, and B. Arnaldi, "A New Application for Saliency Maps: Synthetic Vision of Autonomous Actors," in *Image Processing, 2003. ICIP 2003. Proceedings. 2003 International Conference on*, 2003.

[93] Y. Kim, M. Van Velsen, and R. W. Hill Jr, "Modeling dynamic perceptual attention in complex virtual environments," *Intelligent Virtual Agents*, 2005.

[94] H. Grillon and D. Thalmann, "Simulating gaze attention behaviors for crowds," *Computer Animation and Virtual Worlds*, vol. 20, no. 2-3, pp. 111–119, Jun. 2009.

[95] S. Okazaki and S. Matsushita, "A study of simulation model for pedestrian movement with evacuation and queuing," *Engineering for Crowd Safety*, 1993.

[96] A. Kamphuis and M. H. Overmars, "Finding paths for coherent groups using clearance," in *Proceedings of the 2004 ACM SIGGRAPH Symposium on Computer Animation.* Utrecht University, 2004.

[97] J. van den Berg, S. Patil, J. Sewall, D. Manocha, and M. C. Lin, "Interactive Navigation of Multiple Agents in Crowded Environments," in *2008 symposium on Interactive 3D graphics and games.* University of North Carolina, 2008.

[98] Q. Song and N. Kasabov, "ECM-A novel on-line, evolving clustering method and its applications," in *Proceedings of the fifth biannual conference on ...*, Department of Information Science, University of Otago. unknown, 2001.

[99] D. Wilkie, J. van den Berg, and D. Manocha, "Generalized velocity obstacles," in *Intelligent Robots and Systems, 2009. IROS 2009. IEEE/RSJ International Conference on*, 2009, pp. 5573–5578.

[100] M. Whittle, *Gait Analysis*, fourth edition ed., ser. An Introduction, M. Whittle, Ed. Butterworth Heinemann, Dec. 2006.

[101] W. Daamen and S. P. Hoogendoorn, "Controlled Experiments to Derive Walking Behaviour," *Journal of Transport and Infrastructure Research*, vol. 3, no. 1, pp. 1–19, 2003.

[102] N. Pelechano, C. Stocker, J. M. Allbeck, and N. L. Badler, "Being a Part of the Crowd: Towards Validating VR Crowds Using Presence," in *Multiple values selected*, Estoril, Portugal, Jan. 2008, pp. 1–7.

[103] X. Pengfei, M. Lees, H. Nan, and V. Viswanathan, "Validation of Agent-Based Simulation Through Human Computation : An Example of Crowd Simulation," in *12th International Workshop on Multi-Agent-Based Simulation*, X. Pengfei, M. Lees, H. Nan, and V. Viswanathan, Eds. Teipei, Taiwan: School of Computer Engineering, NTU, May 2011, pp. 1–12.

[104] N. W. F. Bode, A. U. Kemloh Wagoum, and E. A. Codling, "Human responses to multiple sources of directional information in virtual crowd evacuations," *Journal of The Royal Society Interface*, vol. 11, no. 91, 2014. [Online]. Available: http://rsif.royalsocietypublishing.org/content/11/91/20130904.abstract

[105] D. O. Hebb, *The Organization of Behavior*. John Wiley & Sons Inc, 1949.

[106] A. D. Baddeley and G. J. Hitch, "Working memory," in *The psychology of learning and motivation*, G. Bower, Ed. New York: Academic Press, 1974, pp. 47–89.

[107] E. Lindberg and T. Gärling, "Acquisition of locational information about reference points during locomotion with and without a concurrent task: Effects of number of reference points," *Scandinavian Journal of Psychology*, vol. 22, no. 1, pp. 109–115, 1981.

[108] S. Garden, C. Cornoldi, and R. H. Logie, "Visuo-spatial working memory in navigation," *Applied Cognitive Psychology*, vol. 16, no. 1, pp. 35–50, 2002. [Online]. Available: http://dx.doi.org/10.1002/acp.746

[109] T. Meilinger, M. Knauff, and H. H. Bülthoff, "Working memory in wayfindingâĂŽÃĎÃőa dual task experiment in a virtual city," *Cognitive Science*, vol. 32, no. 4, pp. 755–770, 2008.

[110] M. J. Sholl and S. K. Fraone, "Visuospatial Working Memory for Different Scales of Space: Weighing the Evidence," in *Human Spatial Memory: Remembering Where*, G. L. Allen, Ed. Lawrence Erlbaum Associates, Publishers, 2004, pp. 67–100.

[111] K. Lynch, *The image of the city.* The M.I.T. Press, Cambridge, MA, 1960.

[112] A. W. Siegel and S. H. White, "The development of spatial representations of large-scale environments," ser. Advances in Child Development and Behavior, H. W. Reese, Ed. JAI, 1975, vol. 10, pp. 9 – 55. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0065240708600075

[113] T. Ishikawa and D. R. Montello, "Spatial knowledge acquisition from direct experience in the environment: Individual differences in the development of metric knowledge and the integration of separately learned places," *Cognitive Psychology*, vol. 52, no. 2, pp. 93 – 129, 2006. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0010028505000733

[114] S. D. Moeser, "Cognitive mapping in a complex building," *Environment and Behavior*, vol. 20, no. 1, pp. 21–49, 1988. [Online]. Available: http://eab.sagepub.com/content/20/1/21.abstract

[115] B. Kuipers, "Modeling spatial knowledge." *Cognitive Science*, vol. 2, no. 2, pp. 129–153, 1978.

[116] C. HâĹŽâĹĆlscher, S. J. BâĹŽÂžchner, T. Meilinger, and G. Strube, "Map use and wayfinding strategies in a multi-building ensemble." in *Spatial Cognition*, ser. Lecture Notes in Computer Science, T. Barkowsky, M. Knauff, G. Ligozat, and D. R. Montello, Eds., vol. 4387. Springer, 2006, pp. 365–380.

[117] G. Best, "Direction finding in large buildings," in *Architectural Psychology-Proceedings of the conference at Dalandhui, RIBA, London*, 1970, pp. 72–75.

[118] J. Weisman, "Evaluating architectural legibility: Way-finding in the built environment," *Environment and Behavior*, vol. 13, no. 2, pp. 189–204, 1981. [Online]. Available: http://eab.sagepub.com/content/13/2/189.abstract

[119] T. Gärling, E. Lindberg, and T. Mäntylä, "Orientation in buildings: Effects of familiarity, visual access, and orientation aids." *Journal of Applied Psychology*, vol. 68, no. 1, p. 177, 1983.

[120] G. W. Evans and K. Pezdek, “Cognitive mapping: Knowledge of real-world distance and location information.” *Journal of Experimental Psychology: Human Learning and Memory*, vol. 6, no. 1, p. 13, 1980.

[121] P. Thorndyke and F. Yekovich, “A critique of schema-based theories of human story memory,” *Poetics: Journal of Empirical Research on Literature*, vol. 9, pp. 23–49, 1980.

[122] S. Gopal, R. L. Klatzky, and T. R. Smith, “Navigator: A psychologically based model of environmental learning through navigation,” *Journal of Environmental Psychology*, vol. 9, no. 4, pp. 309 – 331, 1989. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S027249448980012X

[123] B. Kuipers, D. G. Tecuci, and B. J. Stankiewicz, “The skeleton in the cognitive map: A computational and empirical exploration,” *Environment and Behavior*, vol. 35, no. 1, pp. 81–106, 2003. [Online]. Available: http://eab.sagepub.com/content/35/1/81.abstract

[124] M. J. O’Neill, “Effects of familiarity and plan complexity on wayfinding in simulated buildings,” *Journal of Environmental Psychology*, vol. 12, no. 4, pp. 319 – 327, 1992. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0272494405800805

[125] D. R. Montello, M. Hegarty, A. E. Richardson, and D. Waller, “Spatial Memory of Real Environments, Virtual Environments, and Maps,” in *Human Spatial Memory: Remembering Where*, G. L. Allen, Ed. Lawrence Erlbaum Associates, Publishers, 2004, pp. 251–285.

[126] R. Kaplan and S. Kaplan, “Cognition and environment: functioning of an uncertain world. ulrich’s bookstore,” *Ann Arbor*, 1983.

[127] M. â. Persson, “Minecraft,” may 2009. [Online]. Available: https://minecraft.net/

[128] SpaceManiac, “Permissionsbukkit,” Sept 2012. [Online]. Available: http://dev.bukkit.org/bukkit-plugins/permbukkit/

[129] V. Viswanathan, “Game analyser minecraft plugin,” June 2013. [Online]. Available: https://github.com/vaisaghvt/GameAnalyserMinecraftPlugin

[130] Zyph, “Royal palace map,” May 2011. [Online]. Available: http://www.planetminecraft.com/project/royal-palace/

[131] J. Ondřej, J. Pettré, A.-H. Olivier, and S. Donikien, “A Synthetic-Vision Based Steering Approach for Crowd Simulation,” *ACM Transactions on Graphics (TOG) - Proceedings of ACM SIGGRAPH 2010*, vol. 29, no. 4, Jul. 2010.

[132] J. van den Berg, S. J. Guy, and M. C. Lin, “Reciprocal n-Body Collision Avoidance,” *Robotics Research*, 2011.

[133] J. van den Berg, M. C. Lin, and D. Manocha, “Reciprocal Velocity Obstacles for real-time multi-agent navigation,” in *Robotics and Automation, 2008. ICRA 2008. IEEE International Conference on*, 2008, pp. 1928–1935.

[134] H. Xi, S. Lee, and Y.-J. Son, “An Integrated Pedestrian Behavior Model Based on Extended Decision Field Theory and Social Force Model,” in *2010 Winter Simulation Conference*, Nov. 2010, pp. 824–836.

[135] G. Peng and X. Ruihua, “3-Tier Architecture for Pedestrian Agent in Crowd Simulation,” *Pedestrian and Evacuation Dynamics 2008*, no. Chapter 53, pp. 585–595, Dec. 2009.

[136] D. Helbing, I. Farkas, and T. Vicsek, “Simulating Dynamical Features of Escape Panic,” *Physical Review E*, vol. cond-mat.stat-mech, Sep. 2000.

[137] P. Fiorini and Z. Shiller, “Motion planning in dynamic environments using the relative velocity paradigm,” in *Robotics and Automation, 1993. Proceedings., 1993 IEEE International Conference on*, 1993, pp. 560–565.

[138] S. J. Guy, M. C. Lin, and D. Manocha, “Modelling Collision Avoidance Behavior for Virtual Humans,” in *9th Int. Conf. on Autonomous Agents and Multiagent Systems (AAMAS 2010)*, Toronto, Canada, May 2010, pp. 575–582.

[139] S. Luke, C. Cioffi-Revilla, L. Panait, K. Sullivan, and G. Balan, “MASON: A Multi-Agent Simulation Environment,” *Simulation : Transactions of the society for Modeling and Simulation International*, vol. 82, no. 7, pp. 517–527, 2005.

[140] J. Snape, J. van den Berg, S. J. Guy, and D. Manocha, “Independent navigation of multiple mobile robots with hybrid reciprocal velocity obstacles,” in *Intelligent Robots and Systems, 2009. IROS 2009. IEEE/RSJ International Conference on*. IEEE Press, Oct. 2009, pp. 5917–5922.

[141] B. Banerjee and L. Kraemer, “Evaluation and Comparison of Multi-Agent Based Crowd Simulation Systems,” *Agents for games and simulations II*, pp. 53–66, 2011.

[142] A. Lerner, Y. Chrysanthou, A. Shamir, and D. Cohen-Or, “Data Driven Evaluation of Crowds,” *Motion in Games*, pp. 75–83, 2009.

[143] ——, “Context-Dependent Crowd Evaluation,” *Computer Graphics Forum*, vol. 29, no. 7, pp. 2197–2206, Oct. 2010.

[144] L. Von Ahn, "Human computation," in *Proceedings of the 4th international conference on Knowledge Capture.* Carnegie Mellon University, Pittsburgh, PA USA, Oct. 2007.

[145] J. D. Sterman, "Testing Behavioral Simulation Models by Direct Experiment," *Management Science*, vol. 33, no. 12, pp. 1572–1592, Dec. 1987.