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

Vaisagh Viswanathan T

Dec 2011

Nanyang Technological University, Singapore

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Chapter 1

Introduction

In this thesis, the author proposes to create a multi agent based model of crowds engaging in egress which is based on the idea of humans being serial information processors. The model will take into consideration the most current research in human and crowd behavior and integrate this into a model that can simulate the evacuation of thinking, feeling and forgetful humans from a building. The model considers the entire process of evacuation from the point of start of fire to the point where the last person exits.

Modeling crowds and simulating their behavior and movement has become popular in recent times and is being used for a wide range of applications. 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 [1]. 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.

These software that simulate crowds are necessarily very complex because the scenario of a crowd evacuating from a stadium or an airport, is itself a very complex system with lots of interacting elements (including people, fire, escalators, etc.) each of which can cause different complications in the system. However, over the years, many models have been developed and perfected. For example, 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 [3–5]. 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 social sciences and humanities [4, 5]. Many details of human behavior are wrongly abstracted away, when in fact they actually play a very important role in determining the evacuation dynamics.

One such example of an abstraction often applied to models of crowds is the perception system used by the modeled humans. More often than not, only a simple visual perception system that perceives all other humans and objects within a certain distance to the agent is used. There are two problems with this approach. The first one is obvious; humans have other methods of observing the environment including aural and olfactory perception. The second problem arises because of a limitation of the human brain. It can only process a limited amount of information at any given point of time. This limitation is something that we come across constantly in our everyday life but which we often fail to notice. For example, while sitting engrossed in reading a book it might take a while before we notice someone calling us. It is also because of this same reason, that we are able to listen and understand someone better if we close our eyes and listen. It is also using this same principle that magicians perform their magic tricks without the audience noticing the trick.

How is this limitation important in modeling a fire evacuation? This can affect the way in which 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; they are actually just reacting rationally to the limited information that they have [4, 6–10]. At the individual level, the difference caused by this can be as little as a few seconds delay in starting evacuation. From the perspective of someone looking at the whole fire evacuation system including the building, fire, fire alarms, people, etc. i.e. the complex system, this is just a microscopic difference. However, when multiplied over an entire crowd of people that are in a building, the effects can be profound. Recently, experts in various fields have realized the importance of acknowledging that most systems in the world are complex systems and these complexities need to be acknowledged and modeled to have any hope of actually understanding and predicting what happens in the real world. One such expert is the illustrious economist Dr. Brian Arthur who is a vocal critic of the major trend in economics to assume the prevalence and importance of equilibrium [11]. He is of the opinion that systems can never attain an ideal equilibrium because of the complex system of interactions present in any economic system.

Modeling such a complex system is not generally a simple task. One of the most popular methodologies for this is by modeling it as an Agent Based Model (ABM). ABM are generally made up of multiple heterogeneous intelligent entities known as agents. Since each agent's behavior can be specified, this method often allows the modeler to implement psychological or microeconomic theories directly without having to abstract away too many details. 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 watch it work. Higher level patterns that emerge from this micro modeling can be analyzed and studied to learn more things about the system and make predictions.

Crowd and evacuation simulation has been in the radar of modeling and simulating experts for the past few decades. However, due to limitations in the technology available, most approaches like lattice gas models [**?**] and flow models [12] have concentrated on abstracting away the details and getting an approximate result in order to get such details as are necessary for that particular application. Advances in hardware have removed many of these constraints. As a result, models have increasingly become more detailed and capable [13]. At the same time there have been tremendous advancements in our knowledge of human behavior. 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. Another limitation of some models is their tendency to concentrate on a particular aspect of evacuation or a particular phase of evacuation behavior without considering the complete process of evacuation. While this is absolutely necessary, it is also necessary to model the complete process which will be discussed in more detail in Sect. 2.2.4.

1.1 Problem Statement

Several studies over the past few decades have changed our understanding of human behavior during fire evacuations. Some studies [4, 6–10] 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 found the importance of groups [14] and the effect of stress and time constraints on human behavior [15]. Torres's thesis [4] compared and analyzed the effectiveness of various theories in explaining a real life fire scenario. Aguirre [3] gave an excellent criticism of existing computational models of egress and the shortcomings and strengths of different models.

However, there is still no computational model of *the entire process* of egress. 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 [16**?**] behavior are very simple and abstract away too many details.

It can be argued that such a model of the entire process is unnecessary and completeness could be achieved by combining existing detailed partial models. However, in such a case it would be difficult to maintain model *coherence*. While modeling the complete process of egress, care has to be taken to ensure that the model is coherent. In other words, entirely different and unrelated methods shouldn't be used to model different phases of evacuation behavior. Using a single central theme, grounded in our understanding of human behavior, provides a logical consistency to the model that is useful in both understanding and using the model. Besides logical consistency, another problem that can arise in combining existing unrelated models is discussed in Section 2.3.3.3.

In this thesis, a computational model for simulating the behavior of humans during fire evacuation is proposed. The entire process of evacuation is taken into consideration. The central idea that humans are serial information processors [15] are used as the basis for creating and explaining the entire process in the proposed model which we call the *Information Based EVACuation (IBEVAC) Model.*

1.2 Key Contributions and Scope of this Thesis

Some of the key contributions of this confirmation report and this thesis will be:

- A comprehensive multidisciplinary survey and analysis of current literature on fire evacuation and crowd behavior. The major portion of this work has been completed and will be presented as a key part of this confirmation report.

- A novel information based perception system that can model the complexities and limitations of the human perception system. This model has been created and implemented and presented at the CyberWorlds 2011 conference and will be discussed in detail in this confirmation report.

- A novel model of pre-evacuation behavior and the process of information seeking. This phase of evacuation has been proven to exist by social scientists but has been generally ignored in most computational models of egress. A computational model for this phase is proposed and presented in this report but it hasn't been implemented at this stage.

- A landmark based cognitive map of the environment along with a communication system that approximates the way in which actual humans communicate about their knowledge of the environment. Work on this module has only just started. Only the basics of the model is discussed in this confirmation report. It will be elaborated on during the author's PhD candidature and will be a key part of the final thesis.

- A complete computational model of the human behavior process during egress, starting from pre-evacuation doubtfulness to escape planning that is firmly grounded in the latest research information available. The framework of the model and most of the details have been developed and are presented in this report. The model has not been implemented completely yet. So only some of the details of the implementation of the model are discussed in this report.

1.3 Organization of the Report

This report is organized as follows. Chapter 2 provides a comprehensive review of relevant theories and pre-existing models and also provides a critical analysis of some relevant ones. Having presented the current state of the art, the following chapter provides an overview of the overall Information Based EVACuation (IBEVAC) model architecture. Chapter 4 then presents the new Information Based Perception Model and some experiments that demonstrate its capabilities and working. Chapter **??** gives an introduction to the proposed structure and working of the remaining modules of the architecture. Finally, Chapter 7 winds up the report by presenting, in brief, the work that remains to be done and a plan of action for the period of the author's candidature.

Chapter 2

Literature Review

Crowds are typically seen as a large collection of individuals sharing a common location and undergoing some common experience [17]. Depending on the experience being shared, individuals in a crowd can think, behave and react in different ways. In this report 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 reader will be introduced to the current state of research in the understanding and modeling of crowds and, more specifically, emergency egress simulation. 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, Sect. 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 [18]. 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 developments 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: human beings or more generally, crowds.

A spatially proximate collection of individuals undergoing some common experience is generally called a crowd [17]. 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 theory. Torres [4] provides an excellent comparison of the different existing theories of crowd behavior. He goes on to compare 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. 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 identity, social role and the circumstances. There are a lot of studies [4, 10, 15, 16, 19] 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 [19] 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 [15, 16], 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 [6, 20, 21] discuss the effects of culture on egress and others [22, 23] 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.

A model based on social forces [24] uses a significantly lesser amount of abstraction and as a result give more detail. These approaches use formulas and physical concepts that can approximate real life behavior. There are also much more detailed models of egress simulation that model humans as heterogeneous agents that think and act rationally with memory and emotions. These different modeling techniques and models and their strengths and weaknesses will be discussed in more detail in Sect. 2.3.

However, some studies [3–5] 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 [13] have made a start in this direction by recognizing the need for behavioral models. However, as stated by Sime in [5]

> 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 behavioral model proposed in [13], but studies have shown that this concept is neither clearly explained [4] nor well accepted [5, 9, 21, 25–27]. Also, it is difficult to find computational models that model the *pre-evacuation behavior* of the evacuees.

Our knowledge of human behavior, emotion, social interactions and decision making is constantly expanding and evolving. As a result, a much more complex picture of human behavior has been emerging. In trying to use this knowledge in making a computational model that is feasible, it was often necessary to abstract away certain details from this complex picture. But with current advancements in technology, this needs to be done less. 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 in mind, 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 Sect. 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 [9, 21, 27, 28] and the constant search for information [10, 15, 29, 30]. In this section, the reader is introduced to some of the major accepted ideas on the nature of human behavior and some of the major theories on the same.

2.2.1 How does it all begin?

Ideally, when a fire starts, a fire alarm goes off, all occupants hear this alarm, move towards the nearest safe exit and exit from 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 [31]. This uncertainty about the authenticity of a first sign of danger isn't an isolated incident [5, 26, 27, 29, 30, 32–34]. So, when studying the behavior of evacuees, it is necessary to study and understand their actions right from the point the fire started [30] to the point where the last person evacuated (or died). 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 [10]. 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 telling you to escape are also cues. There are three kinds of cues [10]:

- 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 [27, 35] an ambiguous cue by itself does not cause a person to initiate investigation into matters. 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 [30] even the 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 sections.

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 [10]. The classic study presented in [?] 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 Sect. 2.2.2. Various studies [9, 21, 26, 29, 30, 36] 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 [19, 21, 30] that discuss these intrinsic factors. Andrée and Eriksson's report [20] 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 [6], 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 [6, 9, 21]. 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 [19] 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 [15, 35] have confirmed the importance of this phase, though sometimes they are known by different names. In [15] 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 [30], 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 that 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 [4, 6–10] 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

In the previous section, the effect of groups on cue perception had been briefly discussed. Groups actually have a much more important role to play in evacuation than just being a factor that influences cue perception. Each human is not an isolated individual. Being a social being, he is influenced by the people around him, even when they aren't actually his companions. As stated by Tong and Canter [30]:

> Research on human behaviors in fires reveals the dynamic process actors engage in to deal with an emerging threat. Emergency egress is a complex social process; it is false to assume humans automatically take protective measures upon hearing an alarm or notification that a threat is present in their environment.

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 [4], 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 *Nonadaptive*

Table 2.1: Factors affecting Evacuation Behavior. The list of factors and their influences as presented in Kuligowski's survey [19]

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

Behavior. Nonadaptive 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 before people start panicking. This belief in a generalized threat, develops when people perceive ambiguous cues and then feel anxious due to factors, like a feeling of reduction in exit choices they find a certain unambiguity in believing in a generalized threat which they can counter by fleeing. Also components of social action need to done that permit panic to occur. Components of social action are characterized as being actions that are as per norms (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 refereed to as *keynoting*

- **Non-Social Model** : This theory's main proponent is Quarantelli [37]. 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. [14] 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 [8, 17, 36, 38]. 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 [8] 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 [30] 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 [6]. However, as further highlighted in the same paper by Kobes et al. [6] 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 [39]), 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. [6].

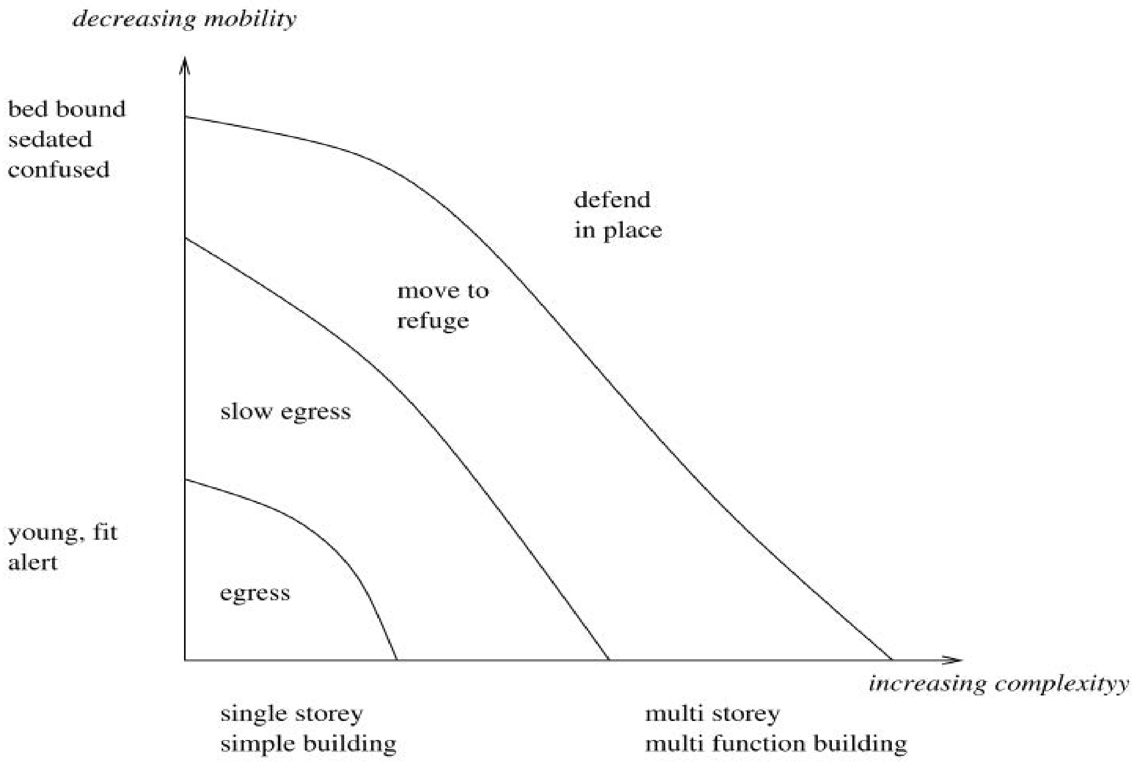


Figure 2.1: According to this chart from [39] there are four strategies that humans resort to in egress. Studies have shown though that more often than not, egress or slow egress are the only strategies taken.

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 [25], who are the main proponents of the self categorization 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 [7, 9, 10]. Several studies [9, 10, 14] actually take a much stronger stand that competitive behavior almost never happens and rather people almost always behave altruistically. This was further confirmed in the thesis which 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 [20, 40, 41], among others, have already demonstrated the important role that social bonds play in behavior during egress. This was reaffirmed by Torres [4], who found that even in cases of extreme danger, people still maintained their social bonds. In fact, as opposed to the non-social model, 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 [4, 6].

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 [9, 21, 26, 29, 30, 36] 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.

Another important point to be noted is the importance of inter group and intra group interactions and how these interactions affect the decisions and behaviors of the individuals in them. The emergent norm theory explains these through a process of milling and keynoting. While this theory can explain many situations, there are certain problems with this approach which are explained quite well in [8]. Most notably, the extended period of milling that is proposed to take place regardless of time constraints. The current understanding [8] is that each person has an individual identity and a group identity. The group identity and the individual identity are highly interconnected in the sense that each individual influences the group's behavior and vice versa. While the importance of leaders in groups is recognized, it does not support the idea of keynoting where only the leader has full power over the 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. So the idea is that people always try to escape but do not try to compete with each other, they look for familiar people or locations in dangerous situations and if possible they form new bonds with strangers stuck in similar situations. Also, the social role of a person determines his behavior. 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 an emergent evacuation scenario is the idea of limited time and the stress/ fear experienced by the participants. The effect of this stress on their behavior will be discussed in more detail next.

2.2.3 What about stress and time constraints?

In this section, the effect of stress and time constraints on egress behavior is discussed. It has been proved [4, 6–10] that very rarely do people panic and behave irrationally in spite of time constraints and stress. But the question that might arise is why people do not take the best possible actions and always act in their best interests [21].This is 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 [42]:

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 [32].

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 [15] 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 [15] 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. 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 [34, 43].

- 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. On the other hand, cues provided by official sources are given a lot of credence. 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

- Stress and time constraints have an impact: 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.

- Groups are important: Groups and social bonds form an important part of determining the person's behavior and decisions. People within a group exchange information and groups also pass on information to other groups. Each group then makes decision's based on the groups intrinsic properties and the information available to them which in turn is determined by the characteristics of the individuals who make up the group. Most groups also have a leader who takes the lead in trying to make decisions.

- 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.

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 Engineering Models

Through the modeling and simulation of egress situations 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. In Sect. 2.3.1 the reader is introduced to the different components that constitute a model. In Sect. 2.3.2 the major different kinds of models are introduced along with some of their strengths and weaknesses. And in Sect. 2.3.3 some of the models are explained in more detail.

2.3.1 What are the components required by a computational model of egress

Some of the major components of a complete computational model of egress are the following.

2.3.1.1 A model of the environment or location

To help in egress simulation a complete model should be able to accurately represent the physical environment of the location where egress is taking place. It should be able to store the layout of at least one floor with doorways and passageways represented to scale. It should also be possible to simulate multiple layers for more complicated physical environments. At a lower level, it should also be able to represent the internal details of the rooms, like furniture, etc. Some models [44?] even consider movement across stairs and escalators.

2.3.1.2 A fire or smoke model

It is also necessary 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 [45] gives a compilation of different models that are used for modeling and simulating fires.

2.3.1.3 A model of 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 the next few sections. 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 used shape, size, etc. This is discussed in much detail in a few articles [2, 46]. 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 [46, 47]. 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 surveys [33, 43]. The relationship between speed and density is general a standard measurement made in evacuation scenarios and this relationship is called the fundamental diagram. This is presented in most models of evacuations as a measure of the effectiveness of the model. Some studies [48] compare the differences in movement across cultures.

- Navigation: Navigation refers to how the agents move within an environment. This depends a lot on the kind of model being used and is discussed in more detail in later chapters. It is important to realize that movement in an egress simulation can have complications because of the effects of fire and smoke. Some studies [6, 49?] that explain how the limited visibility causes people to walk along the walls and increases following behavior.

- Knowledge: This is another key factor in models. The more detailed models model individual specific knowledge and exchange of information while the less detailed models sometimes assume complete knowledge of the environment for all the agents.

- 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.

2.3.1.4 A model of management

It is generally recognized that the employees of a place or the people in charge of handling a fire evacuation have a key role to play in fire evacuations [3, 9, 20, 26] and thus they also need to be considered for a model to be termed complete. This model should also include things like the signs or announcements that are made to help people in their evacuation.

In the following sections, some of the different approaches that are used for modeling crowd evacuation is presented. There are hardly any models which have all the components mentioned above, but most models have at least a few of them. If not, their modeling capability is severely limited.

2.3.2 Some existing models and their strengths and weaknesses

There are a lot of reviews of computational models of egress. Some reviews [7, 50–53] 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 [3] give comparisons and critical analyses of some of the most popular models of crowd evacuation simulation. The former gives an analysis from an engineers perspective while the latter analyses the models from a psychologist's perspective. Together they form an invaluable source of information on computational models and their strengths and shortcomings.

There are generally many ways in which crowds and fire evacuations are modeled. Some studies [51, 52] have presented the major differentiating criteria between these models. For example, some models do not model 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 that approximate behavior. While others used rule based techniques. Another 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.

Some reviews [7, 53] 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. [7] explained each approach's strengths and weaknesses in more detail, while [53] lists the different models of each kind and their features.

As mentioned in Sect. 2.1, all these differences can be broadly 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, a multi agent 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.

For a complete and detailed analysis of the features of different models and their differentiating features, the reader is referred to one of the surveys mentioned above. In the following pages, some of the typical models of each approach are introduced and analyzed with respect to the *requirements* of a computational model of egress mentioned in Sect. 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+. In this the user specifies the capacity and initial content for each node and the traversal time and arc flow capacity of each arc. Then Queuing theory is 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. [54] gives another example of a similar queuing theory based approach which has a basic ability to show heterogeneity. But this ability is very limited and for most practical applications, 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 [55]. Evacnet+, [56], [54] are some examples of this approach.

2.3.2.2 Flow models

Schadschneider et al. [7] provided an excellent analysis of these kinds of 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. The first of these models was Henderson's model [12] 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 [55].

2.3.2.3 Smart environments

These models are more complex than the above two and generally manage to model some complexity of behavior. The idea behind these models [57] 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 have "smart" environments.

In [57, 58], the authors propose a smart 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. Though the term smart environments is new, 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 a "smart environment" to implement complex behavior:

2.3.2.3.1 Cellular Automata based approaches: The term CA model is somewhat loosely used in the field of modeling and simulation of crowds. Strictly speaking a CA model is one which is discretized in time and space and the simulation is run in time steps. In each time step the value of each cell is updated based on the values of the cells which are in the specified neighborhood. The neighborhood generally refers to an area of cells within a 1 or 2 cell radius. In the way that it is used in crowd simulation literature, a CA generally means that the physical space (the environment) is divided into cells or grids. The simulation is run in time steps. During each timestep all the grids are updated synchronously. This technique is very popular and has been used in a number of different ways. In [51, 52] these models are called *fine network models*. [**?**] is a typical, simple CA model in which the agent position is updated based on his 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. It is used in the paper 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 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 similar to CA models. In fact they can be considered to be a special kind of CA model that borrows heavily from the flow models mentioned earlier. The evacuation models used in [59?]are some typical examples. They make use of a discretized version of the Boltzmann transport equation for modeling motion. Like CA models, the earlier models used simple square grids while the newer models make use of a hexagonal grid. These models do not 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. As the model uses an approximation of motion, it will not be possible to use such models for the complicated behavior proposed in Sect. 2.2.4

2.3.2.3.3 Floor field models: Floor field models are also CA models. These models are slightly more capable because they can send messages between each other and communicate. The SWARM information model proposed in [60] is an example of a floor field model. In this 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 like points where maps are displayed, the agent can upgrade his 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, but most of the features mentioned in Sect. 2.2.4 is missing. [?] is also a similar model that has a static potential field guiding towards the goal and a dynamically generated interaction field. It also shares the same limitations.

The Situated Cellular Automata (SCA) modeling framework [61] was proposed so that it 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 smart environment 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 models like this (especially the SCA model) might, in the future, be extended to model complicated high level behavior of the kind mentioned in Sect. 2.2.4 it is not a very intuitive approach. It is more natural for people to think of communication as taking place from one person to another rather than as something that takes place through messages left in the environment. Due to this limitation it might be difficult for psychologists or sociologists, who are not used to computational models to extend this model effectively. Also using the environment for communicating puts severe limitations on the complexity of the communication and interaction that can take place between the interacting agents.

2.3.2.4 Multi agent based approaches

Several articles [62–64] talk extensively about how a multi agent based simulation can most naturally describe a complex system and can be used to study and understand behavior that emerges in these systems. Due to their inherent ability to model heterogeneity and complexity, multi agent systems based models tend to have the most complicated behavioral models. For example, [65] is a NetLogo based agent based simulation notable for having modeled the *management* mentioned in Sect. 2.3.1. This is done by giving the role of officers to certain agents and these officers go about instructing people to leave and giving them instructions on how to do the same. Other models mode more complicated emotions, behavior, social interaction and decision making. Some of these models are explained in more detail in Sect. 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 [55] 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 A few models in detail

In the previous section the reader was introduced to some of the popular approaches to crowd simulation. But very few of the models mentioned above manage to model behavior to the extent necessary. In this section, the reader is introduced to models that manage to simulate some of the key characteristics explained in Sect. 2.2.4.

2.3.3.1 Pires's model of pre-evacuation behavior

Unlike the other models that are described in this section, Pires's model [16] is not a complete model of egress behavior. Nevertheless, it is an important model because it proposes a method by which the entire 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 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 on 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 en 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 like communication, alertness, social role, position, effect of location, population density, etc. 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 [46, 47] have shown that an elliptic or a tri-circle model of humans would be more accurate.

Still uses a smart environment (called iSpace) for modeling communication between agents. As mentioned earlier, 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 falls short on quite a few of the characteristics necessary in an accurate model of evacuation during fire (Sect. 2.2.4).

The greatest strength of this model lies in the importance given to data, both for theorizing and validation. Also, the accurate physical model used, which in turn required 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 [22] is most notable for the approach that they have taken to modeling complex behavior. In order to obtain believable emergent behavior the authors integrated a popular psychological model of human beings (PMFServ) into their existing Crowd Simulation System (MACES).

Their 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 [24] for collision avoidance.

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 [66] and the OCC model [67]. 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 modelling for agents as well. For example, appraisal theory based approaches are also used in certain Agent Based

Models [23].

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 fulfill any of the characteristics of an egress model highlighted in Sect. 2.2.4. However, it is still of interest to us because of 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 coherent mode.

2.3.3.4 Collective Panic Behavior Model

França et al. [68], created a simulation model of panic behavior which was based on the hysterical belief theory explained in Sect. 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 in recent years. 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. Agent's 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 [4, 5].

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 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. Finally, the paper does not give details about the physical model of the agents or the environment or the level of detail used. In fact, in trying to model the behavioral aspect of the model accurately the authors seem to have neglected the engineering aspects of the model completely.

2.3.3.5 Exodus

Exodus [69] is one of the most detailed and mature evacuation simulation tool available. It has different packages for building, maritime and aircraft environments. buildingExodus model comprises five core interacting sub-models, these are the occupant, movement, behavior, toxicity and hazard sub models (see Fig. 2.2).

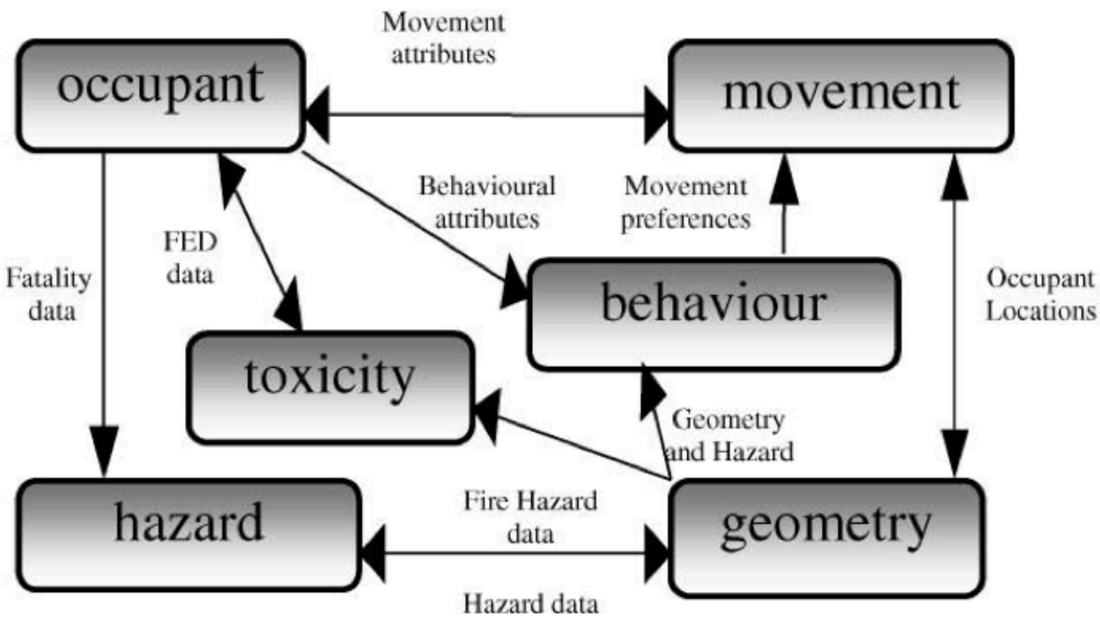


Figure 2.2: Interaction of EXODUS modules [70].

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 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 determines on 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 the hazards like the 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. [70] 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 re-planning is also modeled to indicate the reluctance that people have in changing their pre-decided route.

Hollmann et al. [71] presented a 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. This is an unrealistic expectation. The system should be able to simulate a fair bit of pre-evacuation behavior like emergent investigative behavior and search for familiarity. The current behavior model is quite limited, with new flowcharts and algorithms and new sets of rules required for each new situation. This excessive dependence on rules specified is not a good idea [2].

2.3.3.6 ESCAPES

ESCAPES [72] 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. The reaction time is modeled as a function of the proximity to the event. Agents that are near to 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, that is integral to fire evacuation simulation, it is too simplistic. There is a prevalence of competitive behavior and no idea of social norms. The family sizes are fixed (Parents and two children) and the only social bonds that exist are within this family. There is very limited heterogeneity: All parents and travelers show one kind of behavior and all children show another kind. Despite all these drawbacks, the importance given to affiliation and spread of knowledge is something that should be emulated whenever possible.

2.3.3.7 MASSEgress

Pan's [13] 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 engine modeled 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. The ray tracing algorithm ensures that 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 individuals perception of the system as stressful determines how stressed he is, not just what happens to him. So even in a non emergency situation, *nonadaptive 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 pretty good 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 nonadaptive 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 Sect. 2.2.4 were also presented and analyzed.

- Pires's model [16] 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 [73] which produced higher level herding, following and competitive behavior by using simple lower level rules.

- Pelechano's work [22] 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 [68] demonstrated how a theory of human behavior can be computationally modeled without having to make any abstractions.
- The EXODUS model [69] 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 [72] 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 Sect. 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 Sect. 2.3.4.

Despite the variety and number of models available, there is still a lack of a detailed comprehensive model that takes into consideration the latest psychological and sociological theories of crowd behavior. Such a model, needs to model the perception of cues and their interpretation; the uncertainty felt by evacuees at the beginning of an evacuation and their search for further information; their preference for familiarity and their search for affiliation and finally the implementation of the effects of stress and time constraints without resorting to the standard assumption of panic/ competitive behavior. In the following chapters, by leveraging on the strengths of existing computational models, a computational model for agents which models these behaviors is introduced.

Chapter 3

Information Based Evacuation Agent Architecture: IBEVAC

In the previous chapter, the salient features of the behavior of a crowd engaging in egress during a fire evacuation were introduced. Firstly, 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*. When he realizes that the situation requires some action, he tries to escape. However, he does not try to go directly to the exit. Instead, he first tries to meet up with his primary group members (provided he has one) [4, 10, 17, 40] and only when he is with all of them do they all try to exit together. While trying to exit, *information* still plays an important part. Firstly, unless he is trained for egress, it is unlikely that he will have knowledge of all the exits. As a result, he is most likely to just move to the nearest exit that he knows of. He may change his exit choice if he gains new information either through signs he perceive or through communication with other people engaging in egress (including his own group or personnel in charge of evacuating the place). Time constraints and stress can create distortions in the capacity to process information and produce what seems to an outsider to be irrational behavior (even though it is still rational within the decision maker's frame of knowledge). An overview of this process of human evacuation is illustrated in Fig. 3.1. Whatever action they are undertaking, they preserve social norms as far as possible by not shoving or pushing other people [4, 14, 25].

It is generally recognized that information plays an important part in solving problems [74] and other daily decisions. Chapter 4 explains how information has an important role to play not only in high level decision making but also at the lower level of perception and simple motion. The behavioral model proposed in this report is based on the idea that humans are *"serial information processors"* [15]. Using this underlying theme, a multi-agent based framework called *Information Based*

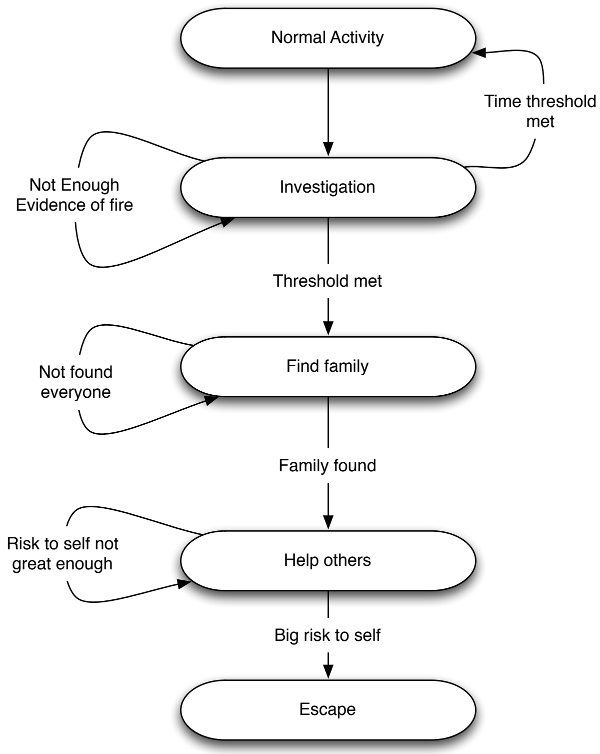


Figure 3.1: The Process of Evacuation: This state diagram shows the different phases of behavior of a person engaging in egress and the triggers that cause phase changes

EVACuation (IBEVAC) model is proposed that is able to model all the characteristics highlighted in the introduction to the current chapter and Sect. 2.2.4. In this chapter, Sect. 3.1 provides the foundation for the proposed architecture by explaining how the egress process can be explained as a combination of 5 sub-processes. This division is used as the basis for the IBEVAC agent architecture that is described in Sect. 3.2.

3.1 The Six Building Blocks of Crowd Behavior during Egress

The fundamental assumption of the proposed model is that the evacuation process, discussed in detail in Sect. 2.2 and outlined at the beginning of this chapter, can be broken down into 6 building blocks: perception, event identification, knowledge, communication, task management and navigation. This section explains how this is possible by defining each of these building blocks and their significance in the evacuation process.

3.1.1 Perception

Perception refers to the process by which a person observes his environment. For an agent, this implies that it should extract features from the environment. These features are called percepts [75]. While an evacuee moves around he makes use of his perception to complete his tasks and avoid collisions and, in general, to behave normally.

In some cases, he might perceive something out of the ordinary like a ringing fire alarm or smoke or even people running away from something. If these special percepts, known as cues, are intriguing enough, then he will set about investigating the environment in search of more cues that would help him decide on a plan of action. The percepts can also be in the form of messages sent to the evacuee from other evacuees.

Each percept (whether it is a cue or not) gives the evacuee certain information about the environment. Being human, each evacuee can only perceive a limited amount of information at any given time. This implies that if he is stuck in a very dense crowd and trying to maneuver his way out, he is unlikely to pay much attention to cues because of an overload of information.

The perception process is the main interface of the agent with the environment through which it gets all the information needed to act. This idea of looking at perception as a process of gathering information is referred to, in this report, as *information based perception.*

3.1.2 Event identification

It was mentioned in the evacuation scenario described above that at some point the evacuees decide that the situation warrants investigation. Later on, the evacuee decides that he has enough evidence and it is time to escape. How do the evacuees decide that they have sufficient information? A person's intrinsic characteristics like his age and gender determine how much information he considers to be enough i.e. his threshold. Each person keeps a track of all the cues that he perceives and when the amount of information crosses the threshold, he starts acting on the evidence. In the first phase mentioned above, this action would be to start investigation and in the second phase it would be the starting of the process of evacuation. In this report, this whole process by which the evacuee perceives, analyses and aggregates cues and identifies an event is called *event identification.* Event identification is the process by which the evacuee decides to proceed to the next phase of evacuation.

3.1.3 Knowledge Base

On recognizing that there is a fire from which he should try and escape, the evacuee tries to find his primary group members and then moves towards his most familiar exit. To keep track of the location of the group members and to keep a track of familiar exits, each evacuee holds his own version of the map of the environment. This personal map is not necessarily accurate. It is dynamic and gradually becomes more accurate as the evacuee explores more of the environment. This sort of evacuee-specific *knowledge* is necessary to model the heterogeneity in behavior found in real life fire evacuations. Thus the knowledge base is where the evacuee stores his knowledge about the environment and its layout.

3.1.4 Communication

Communication, in the context of fire evacuations, is a process that is closely related to the evacuee's knowledge. Through communication evacuees exchange knowledge about events and the layout of the environment. Communication not only helps an evacuee fill gaps in his knowledge and obtain new knowledge, it also helps him confirm his existing accurate knowledge and repair any inaccuracies in his knowledge. Communication is also the process by which trained personnel like the staff and management manage the situation by communicating accurate and important information to evacuees.

3.1.5 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 fire evacuation, navigation is generally considered to be the process of planning a route towards an exit and following that route. However, as explained in the previous chapter, the evacuation process does not simply involve the evacuee moving towards the exit. Rather, there is a pre-evacuation period, where the evacuee gathers knowledge about the situation and finds his primary group members. Depending on the current phase and knowledge of the environment, the goals can be different from this too. So, we define navigation more broadly as the process by which an evacuee plans his route towards a *goal location* based on his knowledge and moves towards this location.

3.1.6 Task management

Almost all the behavior in the scenario above can be explained using the five mechanisms explained above. So where does task management come in the picture? At any given point of time in the simulation, the evacuee is highly likely to have more than one task; each with a different priority. For example, once the person decides to evacuate, he will have at least two tasks to complete: gather his groupmates and move towards the closest exit. The person will try to find his group members as much as possible, until some point, where the risk from the environment is such that he can do nothing but escape. In other cases, there might be a chance to investigate or communicate with someone and find out a nearer or less crowded exit. This task might then take priority over the others. This sort of dynamic task management which is dependent on the perceived time constraint and stress, the evacuee's individual characteristics and his current progress in egress is can also be considered to be parts of

Table 3.1: The Building Blocks of Human Behavior during Egress

Building Block	Definition	Purpose
Perception	The process of gathering information about the environment	Enables the evacuee to avoid collisions, learn about the environment and observe events
Event Identification	The process by which the evacuee perceives, analyses and aggregates cues and identifies an event	Enables the evacuee to change from one phase to another based on current knowledge and internal state
Knowledge Base	The place where the evacuee stores his knowledge about the environment and its layout.	Maintains each evacuee's personal knowledge of the environment thus enabling heterogeneity in the model
Communication	The process of knowledge transfer between evacuees	Enables the exchange of information between evacuees and management by trained staff
Navigation	The routing and movement process	Enables movement towards the evacuee's current goal
Task Management	Higher level management of strategies and tasks for each phase	Simplifies the handling of multiple tasks to be completed at each phase of the evacuee's pre-evacuation and evacuation behavior

task management.

A degree of organization can be brought about in task management by grouping together tasks in a higher level *strategy* implementation. Each strategy consists of a few tasks. For example, the strategy *escape* will include tasks to find friends, to communicate with other evacuees to find out more about the hazard and the quickest path to exit. *Task management* refers to the way in which the evacuees manage to fulfill tasks as much as possible within the constraints put on them by the environment.

In summary, information based perception along with event identification, knowledge, communication, navigation and a higher level task management can together be used to produce the entire process of a human evacuating from a burning building. The function of each of these building blocks is summarized in Table 3.1 In the following section, an agent architecture based on these building blocks is proposed.

3.2 The Agent Architecture

In the previous section, human behavior during a fire evacuation was explained in terms of 6 building blocks. In this section we propose an internal architecture for the agents that will be able to produce the required behavior. Figure 5.1 shows this architecture.

3.2.1 Information Based Perception (IBP) Module

There are many objects or actions that an agent can sense or observe in the environment. We call these *raw percepts*. There are many different ways according to which these raw percepts can be classified. According to the sources, they can be classified as *observations* from the environment and *messages* from other agents.

Observations themselves can either be observations about the static objects in the environment or the actions of other agents in the environment (a group of people running away from something). Regardless of the kind of message, in our model, the Information Based Perception (IBP) module is the only gateway through which the agent receives information from the environment. This module ensures a cap on the amount of information that the agent can process at any given time. Given the kind of information present in the percept, the IBP module passes this on to either the Knowledge Base or the Navigation Module. The working of module is described in detail in Chapter 4.

3.2.2 Knowledge Base

The Knowledge Base is responsible for storing the beliefs of the agent. It stores all the information that the agent currently has about the environment and the situation. This information or knowledge consists of two things: Event Knowledge and the Environment Knowledge.

3.2.2.1 Environment Knowledge Module

The *Environment Knowledge Module* stores the agents personal map. This map is the representation of the layout of the environment that the agent is trying to escape. It is formed as a result of the observations and experiences of the agent in the environment. This module also holds information about the last known locations of the primary group members, so that they can be found in case of an emergency. A confidence value is associated with different areas of the personal map to indicate the amount of confidence the agent has in his own beliefs about the environment. This Environment Knowledge Module also stores information on *landmarks* which indicate areas of the map that the agent believes is accurately represented by itself. This module is discussed in more detail in Sect. **??**.

3.2.2.2 Event Knowledge Module

The Event Knowledge Module stores the agent's beliefs about the current state of the environment. In a fire evacuation scenario, this module stores information on the current stage in egress that the agent is at. It consists of multiple *buckets* of information each with a specified threshold. Each bucket signifies the belief of the agent that a particular stage in egress has been reached. The value of these thresholds are determined by the Agent Description Module. An overflowing bucket triggers the planner to change its current plan. Each event or behavioral cue that the Event Knowledge Module receives is placed into one of the buckets. Once the amount of information available from the cues in the bucket crosses the threshold a trigger is sent to the planner. This module is discussed in more detail in Sect. **??**.

3.2.3 Agent Description Module (ADM)

This module describes the agent. It explains the properties/ characteristics of the agent. This includes the features of the individual like age, gender, speed, mass and height. It also includes a list of the other members of its predefined primary group. The agent also stores its social role which influences the action it takes in the case of different events. Someone with a social role requiring responsibility will have more high priority tasks relating to helping others. As mentioned earlier, all these factors influence the thresholds in the Event Knowledge Module. Some of these factors are given in Table 2.1. This module is discussed mode in Sect. **??**

3.2.4 Planning Module

The Planning Module creates a plan of action for the agent as a set of tasks. In the current scenario each *task* is just a location that the agent has to go to. This goal is passed to the Navigation Module to determine how exactly to get to that location. The Planning module is shaped by the Agent Description Module, triggered by the Event Knowledge Module and informed by the Environment Knowledge Module. Generally, the planning module has *strategies* for normal action, investigation, finding friends, escaping and taking shelter. Each strategy, while not described completely, does give a set of tasks that the agent is supposed to complete for that strategy and this might vary according to the internals of the ADM. The tasks involved in *investigation* would be to find locations of exits and friends and to verify the existence of fire. The planner, based on the information that it has, will determine the location on the map to move to in order to get the next task done and pass this as the current goal to the Navigation Module. By controlling the state of the agent, the planning module is also indirectly responsible for determining communication. Depending on the type of agent and its state a communication trigger is sent to the communication module to communicate messages with other agents. This module is discussed in more detail in Sect. **??**.

3.2.5 Communication Module

The agents are given an ability to communicate with each other when they are in each other's vicinity. They are thus able to transfer their knowledge of exits and hazards in the environment to others. This mechanism of knowledge transfer is not a straightforward procedure because of the inaccuracies in the personal maps of both the agents and their limited confidence in their own and others' personal maps.

This module encodes the information passed to it from the Knowledge Base and converts it into messages that can be perceived by other agents' IBP module. It transmits this messages to agents within a communication range provided some conditions are met. This process of communication is explained in more detail in Sect. **??**.

3.2.6 Navigation Module

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. From the definition, 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.

At the path planning level, the module receives a goal from the Planning Module and it outputs a path that will lead it to this goal. It provides a set of way points to move through to reach this goal. These way points are determined based on the agent's personal map (from the Environment Knowledge Module) and the obstacles that the agent is currently perceiving (from the IBP module). In Fig. 5.1, this module is further broken down into two parts: A higher level path finder that finds abstract logical waypoints towards the goal and a lower level *concrete way point determiner* that translates these logical waypoints to physical locations on the map that the agent can pass through for a collision free path to it's goal.

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. In Fig. 5.1, the motion planning layer ensures that the agent manages to reach its next way point without colliding with another agent. It takes as input the agent's personal space factor from the ADM and the list of obstacles perceived from the IBP and its knowledge of obstacles from the Environment Knowledge Module and outputs a collision free velocity. A review of existing literature in motion planning is provided in Section SectionIBP:MotionPlanning

At the lowest level a Physical Consistency Check Layer is implemented to provide a sanity check for the model. This layer takes as input the velocity proposed by the collision avoidance layer and makes sure that it does not produce unrealistic behavior by ensuring that people cannot pass through other solid obstacles. This layer does not use the personal map for its calculations, rather it uses the actual map as indicated in Fig. 5.1. In the figure, this is drawn outside the agent's architecture because the check is done at a global level and does not use any of the agents' individual charecteristics. The dotted border is to indicate that it is still an integral part of the navigation system used by the agents.

The complete process of navigation is discussed in more detail in Sect. **??**

3.3 Summary

This chapter started with a scenario of what happens to an individual who's involved in a fire evacuation. This was followed by an analysis of the process of evacuation which also proposed how the whole process of evacuation can be explained on the basis of 6 *building blocks*. The next section explained how these 6 building blocks could be translated into an agent architecture. This architecture consisted of *Information Based Perception Module* as a sensor, a *Knowledge Base* consisting of both events and the environment, an *Agent Descriptor Module* which could be used to specify the heterogeneity in the agents, a *Planning Module* for planning and a *Navigation Module* and *Communication Module* as actuators. In the following chapters each of these individual modules will be explained and analyzed in detail. The aim of this report is to develop each of these components to form.

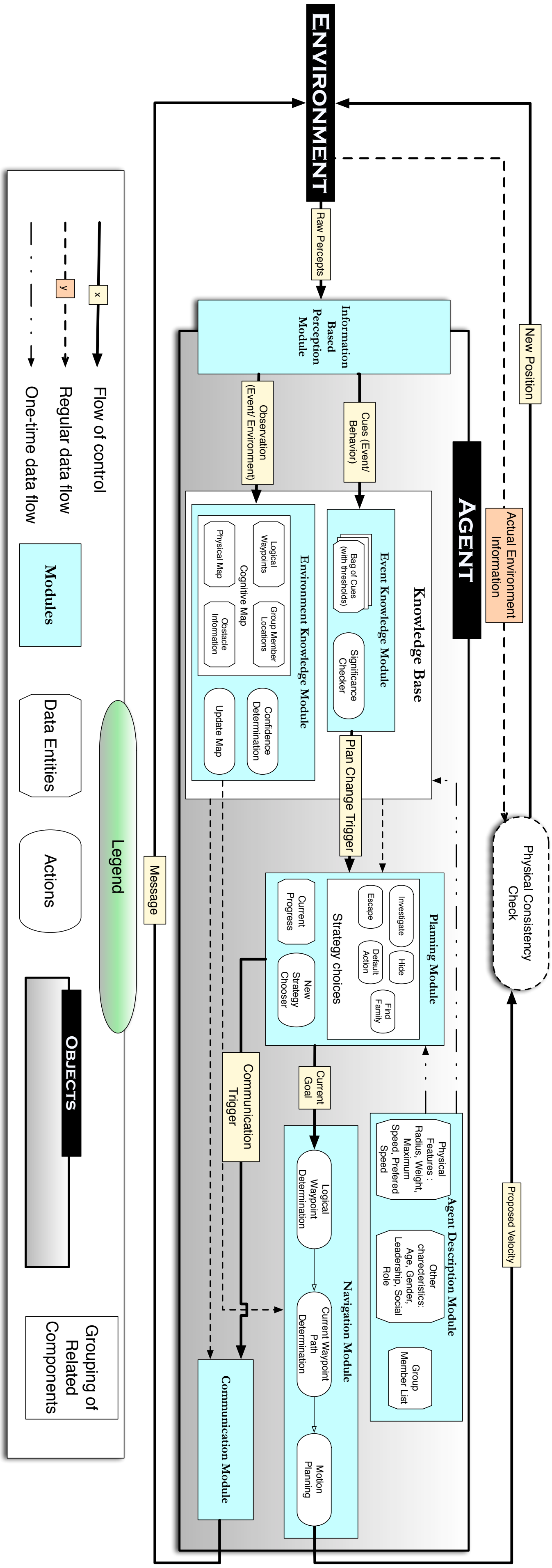


Figure 3.2: An illustrated representation of the agent architecture described in Sect. 3.2

Chapter 4

Information Based Perception

The aim of this thesis is to create an agent based fire egress simulation that models human behavior as accurately as possible. 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 [62, 63]. 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* [75] 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.

As explained in the previous chapter, the proposed IBEVAC agent architecture is based on the central theme that humans are constantly processing information from the environment. The sense-think-act cycle used in agent based modeling is an excellent representation of 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 the perception system of the IBEVAC agent based 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 [76] 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/ her conform to social norms that instruct him/ her 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. It's viability is demonstrated through the implementation of a simple moving agent and by incorporating information based processing into the agent's navigation system. Why navigation only? Besides being one of the major components of Agent Based Crowd Simulation, navigation 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 remainder of this chapter is organized as follows: Sect. 4.1 gives some background on how humans perceive the world around them; the IBP model itself is introduced in Sect. 4.3; following this, Sect. 4.2 presents an analyses some of the existing work in motion planning; in Sect. 4.4 presents the preliminary work done in visual and quantitative validation; finally, Sect. 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 [77] 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 [76] 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 arne'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 [78] 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 [79–81] 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. [80] 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 [82] 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 [83] was one of the first to introduce the importance of cognition in sensing. Courty [84] used a saliency map based approach and Kim et al. [85] used cost-benefit analysis in a decision theory based approach to determining the interest points. Grillon and Thallman [86], this process of interest point determination was automated. 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 LE-

GION [2] and MASSEgress [13] 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 so far 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 the final IBEVAC agent the IBP will also observe events, cues and landmarks from the environment. These will, in turn, be used to learn more about the situation and environment and react appropriately to them.

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 navigation system. It is first necessary to have an idea of existing navigation systems.

4.2 Navigation 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 extracted from Fig. 5.1. It was briefly explained in Sect. 3.2.6 and will be discussed in more detail in Sect. **??**. In this section, *motion planning* is discussed in more detail. It tries to ensure that the human does not go through another human being in the crowd.

There are various different approaches to motion planning. Klein and Köster [**?**] uses an electric potential based model; positive charges are assigned to goals and negative charges to obstacles and agents. Okazaki and Matsushita [87] use a similar approach of using magnetic poles instead of coulombic charges. 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 [24]. In this model, each agent is modeled as a particle that has multiple forces acting on it. 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 [88] more complicated group movement was modeled with an underlying social forces model for collision avoidance.

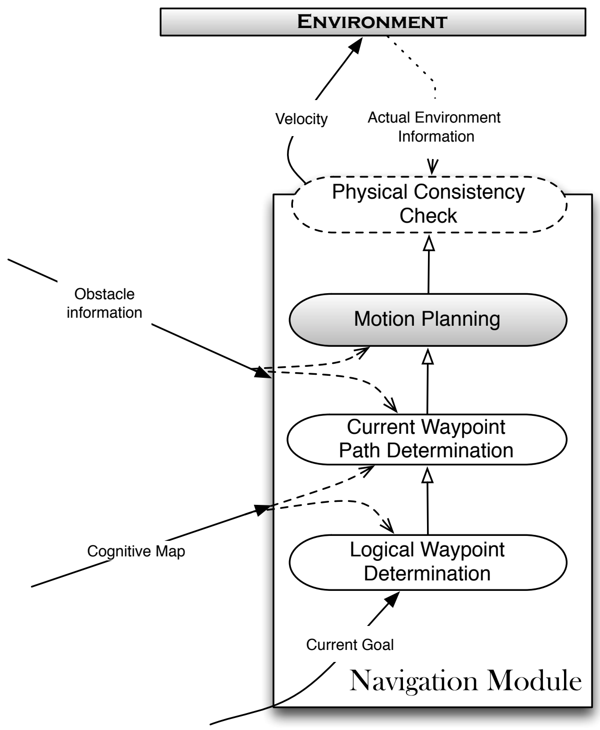


Figure 4.1: Navigation Architecture

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 [89]. Since then there have been several modifications and improvements to the system but the underlying algorithm still remained the same. CLEARPATH [90] which mathematically optimized RVO was the first to introduce a change in the underlying algorithm. Guy et al. [91] 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. [92] introduced a personal space factor and an observation delay made the algorithm more appropriate for virtual humans.

Guy et al. [92] 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 Sect. 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. [92] 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) [93] and computational geometry based RVO2 [94]. 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 $f : Env \rightarrow p*$, 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 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

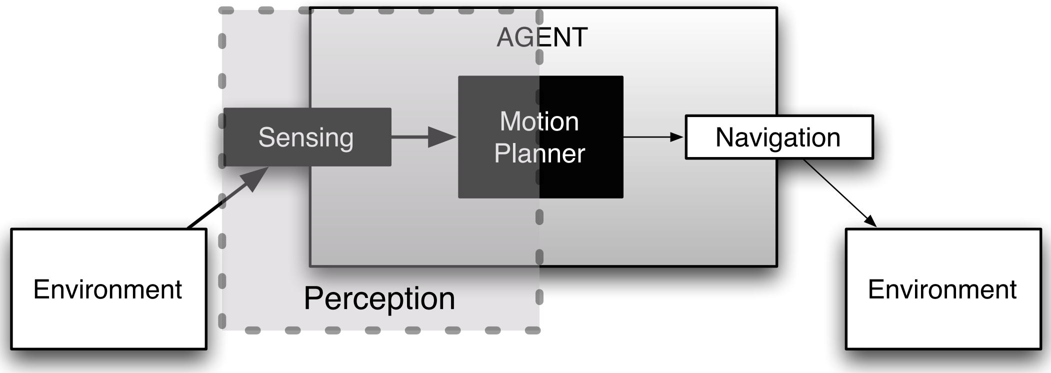


Figure 4.2: An agent perceives and then acts

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 [93] 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 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

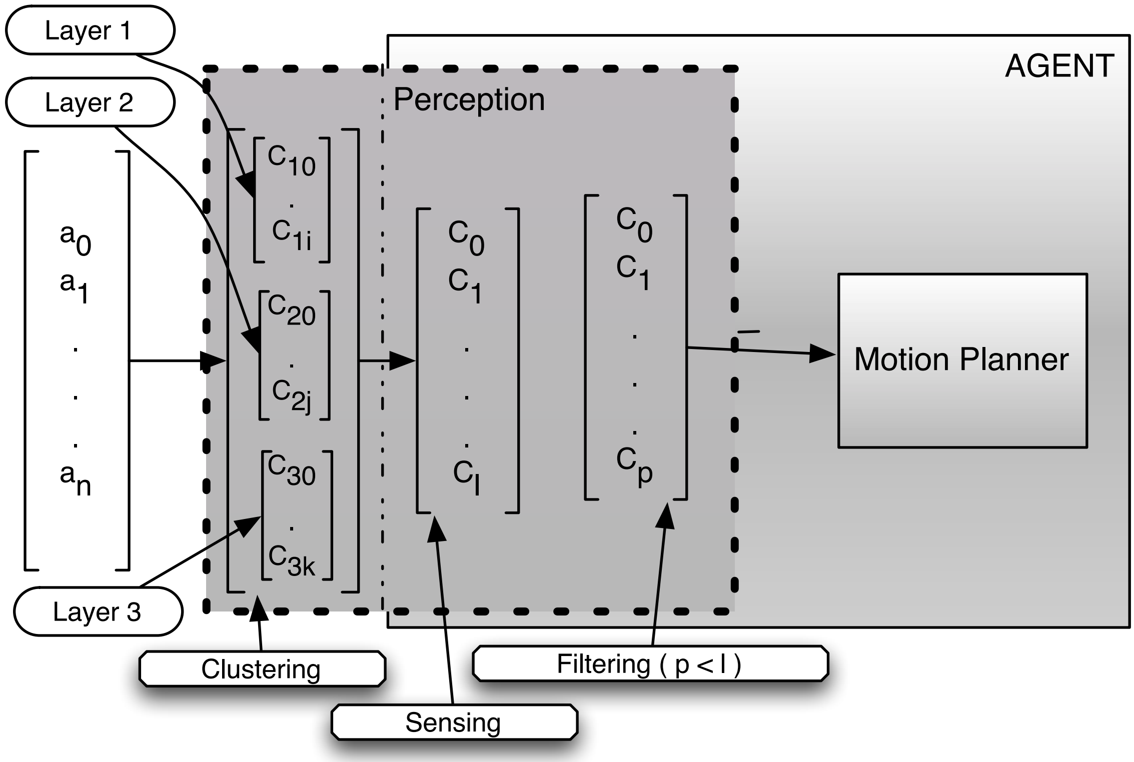


Figure 4.3: Perception in agents takes place through three stages: (1)Clustering is done at a global level. The dotted line indicates this separation. (2) Sensing is the process by which the Agents perceive only a subset of this (3) Filtering further reduces the size of this list and models human visual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

single agent as the first cluster, the maximum clustering radius for layer i, r^i_{max} is fixed (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[1] 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 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

[1]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.

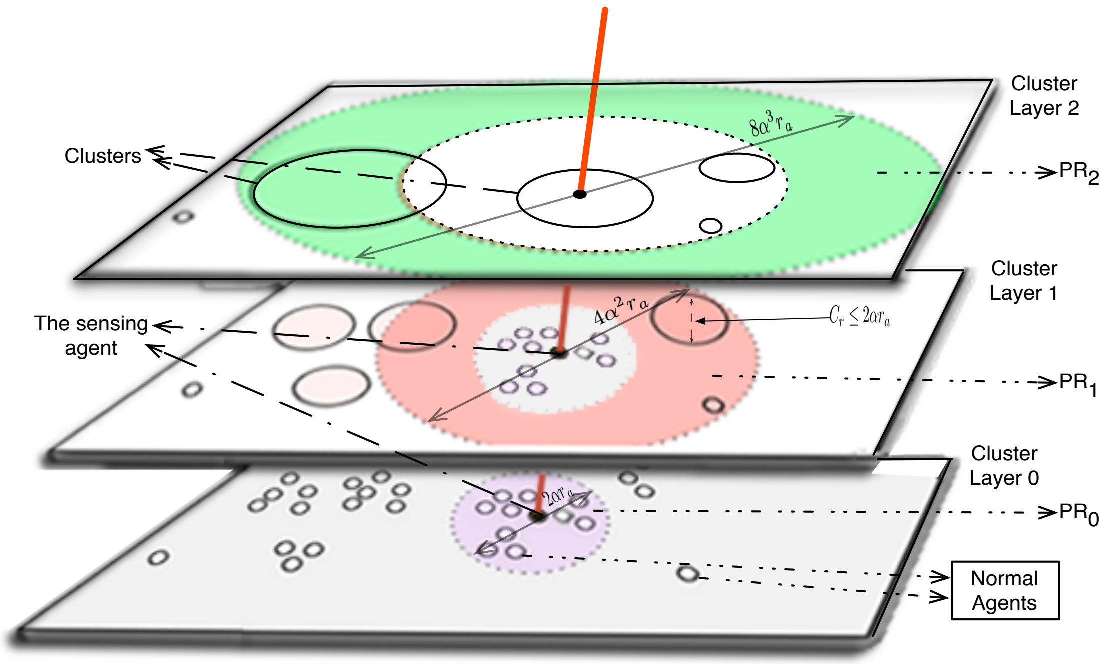


Figure 4.4: The figure illustrates how the opaque agent senses objects using 2 clustering layers. The bottom layer is the original environment and the two planes above show the two clustering layers. Clusters in layer 2 are generally bigger than in layer 1. Solid lined circles indicate the normal agents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

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 [15].

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

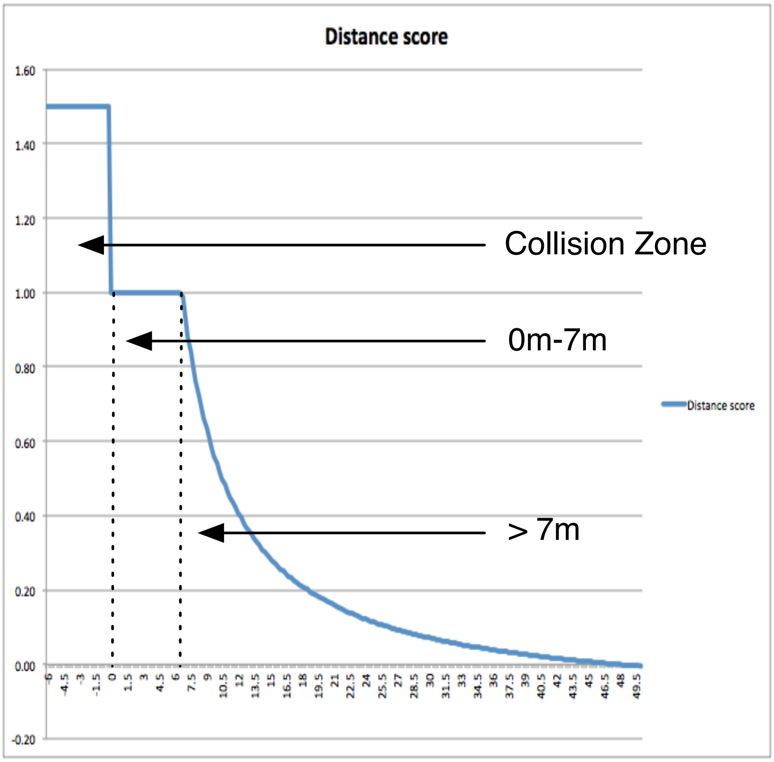


Figure 4.5: This graph shows the variation of distance score with distance (in metres) used in experiments. A score of 1.5 if a collision has already occured, a score of 1 if it is within 7m and an exponentially decreasing score beyond that distance

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 and this will be discussed in Sect. 4.5.

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

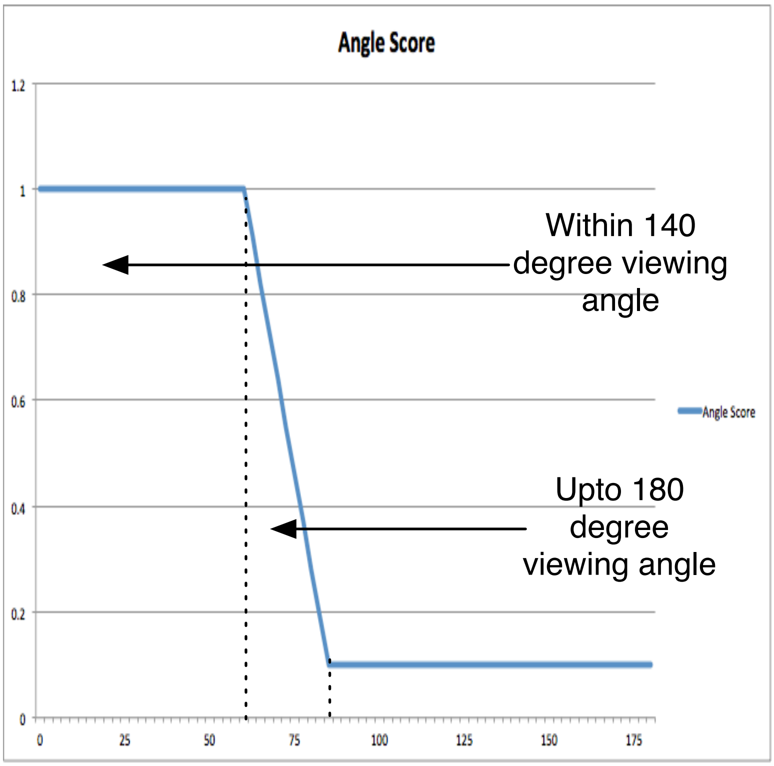


Figure 4.6: This graph shows the variation of angle score with the angle(in radians) formed by the object with the agent used in experiments. For objects forming an angle of less than 70° (viewing angle 140°, a score of 1 is given. For objects forming an angle of up to 90°, the score linearly decreases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

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 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 [91] 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 Results

Eventually, real world data, which would ideally be used for validation of the IBP model, will be collected. Nevertheless, this section presents a preliminary visual and quantitative validation of the IBP model. 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 based approach to motion planning [92], Guy et al. used a measure of effort expended to demonstrate the usefulness of their model. This effort was calculated as follows:

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

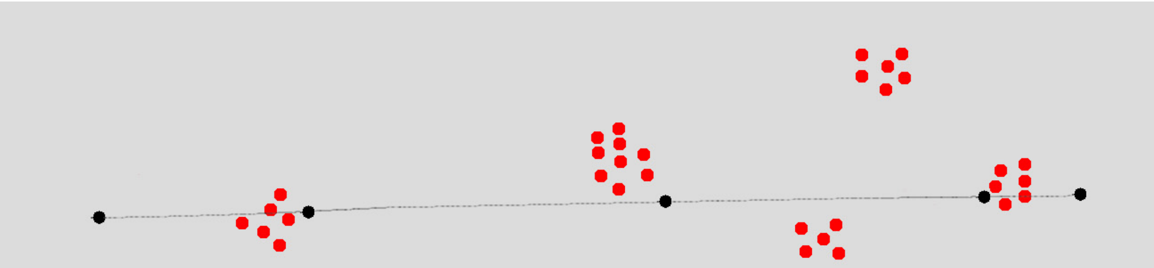
In this section, the same measure of effort is used to analyze and validate the proposed IBP model. For simplicity, all agents are taken to have the same average mass of 70 kg. However, this only measures the mechanical effort involved. To measure the amount of effort spent in decision making, an *inconvenience 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 GBP in modeling the information processing limits of human beings is shown. Finally, the importance and relevance of the information threshold is demonstrated by demonstrating the effect that it can have on an agent.

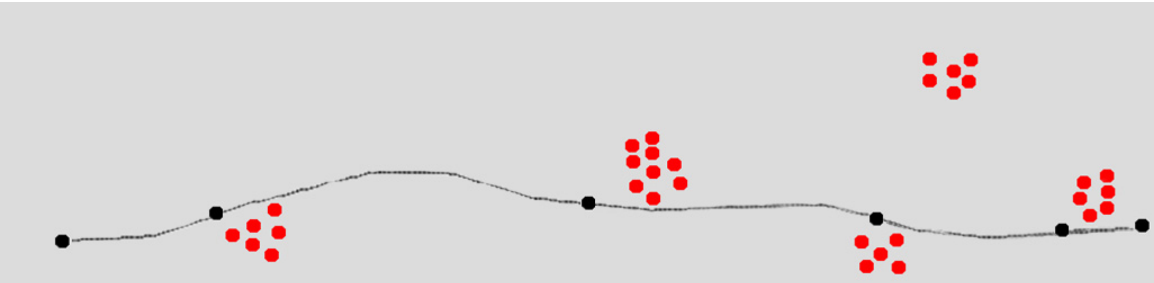
4.4.1 Group Based Perception

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

[2] $e_s = 2.23\frac{J}{Kgs}$ and $e_w = 1.26\frac{Js}{Kgm^2}$ for an average human [95]



(a) Traditional Circular Sensor Range



(b) Group Based Perception

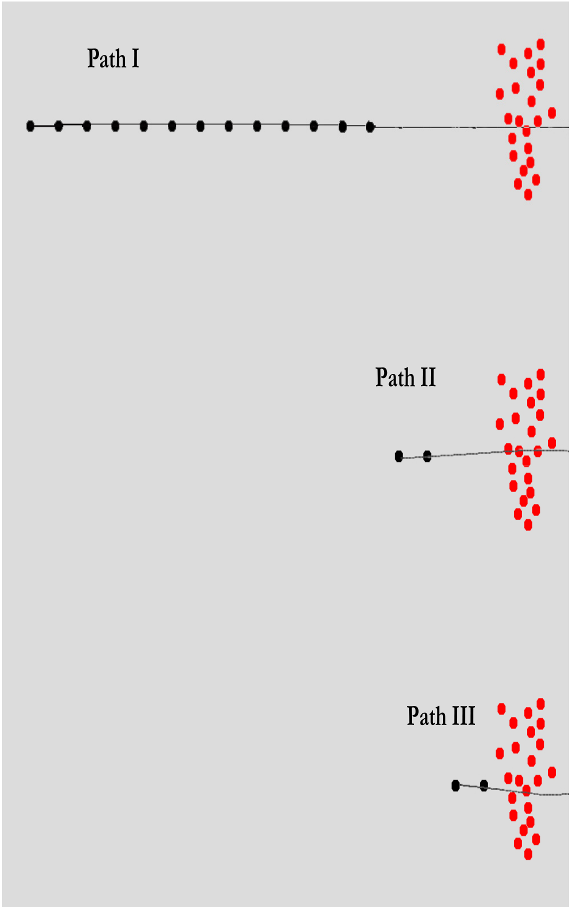
Figure 4.7: Experiment 1: Group Based Perception

Table 4.1: Quantitative analysis of Group Based Perception

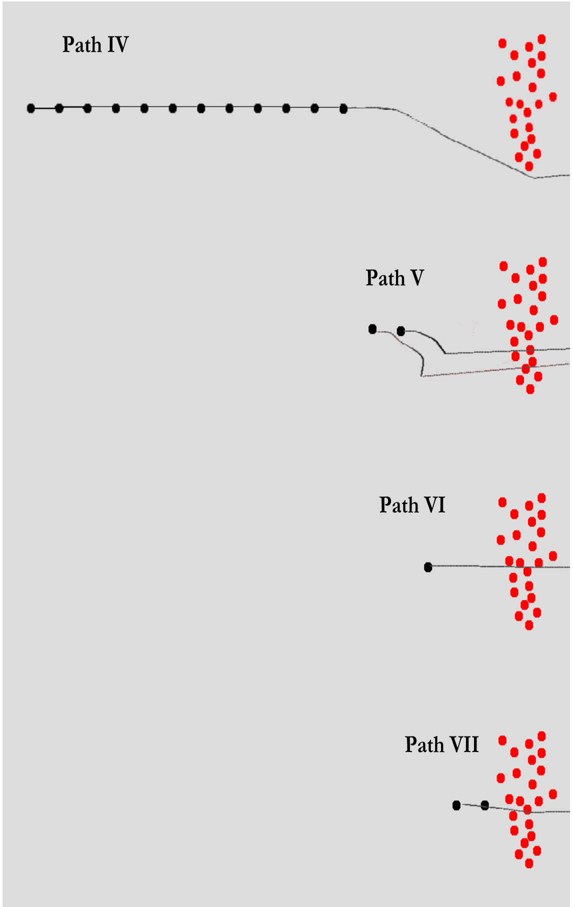
Agent Considered	Effort ($Jm^{-1} * 10^5$)		Inconvenience Cost	
	Without GBP	With GBP	Without GBP	With GBP
Black Agent	71730	71726	120	148
All other agents (average)	1884	1880	14.28	6.56

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 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



(a) Using traditional sensing



(b) Using Group Based Perception

Figure 4.8: Experiment 2: Effect of multi layered clustering

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.

4.4.2 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

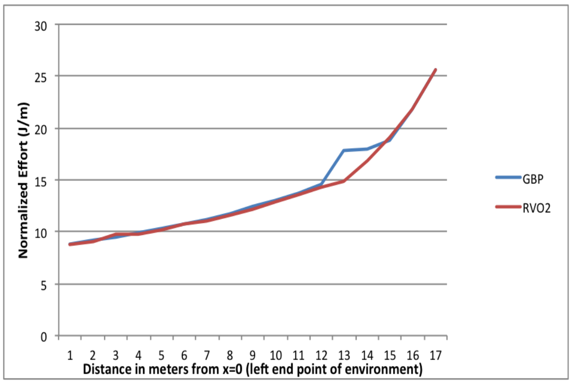
Based Perception does not interfere with RVO2's functioning.

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.

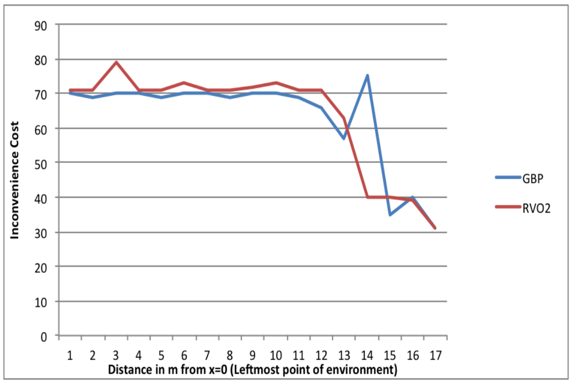
When GBP isn't used, the path followed does not change significantly with distance. The agents in the path of the black agent, give way to the agent, and the black agent just proceeds straight through the center of the large group (Path I in Fig. 4.8a). In the last few cases (Paths II and III), the path 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 it is forced to slow down in the process.

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.

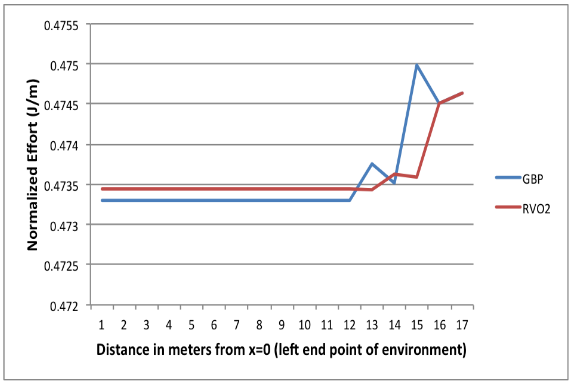
Figures 4.9a and 4.9c show a comparison of the effort expended by the black agent and the average effort expended by all the remaining agents while using a traditional sensor range and GBP. As in the previous experiment (Sect. 4.4.1) there is hardly any difference in the effort expended in both scenarios (except for a slight increase for path V). However, an interesting pattern can be observed in the inconvenience measurement (Figures 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



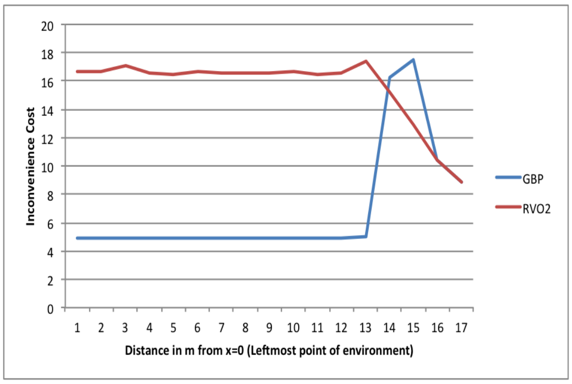
(a) Black Agent- Effort



(b) Black Agent- Inconvenience



(c) Remaining Agents- Effort



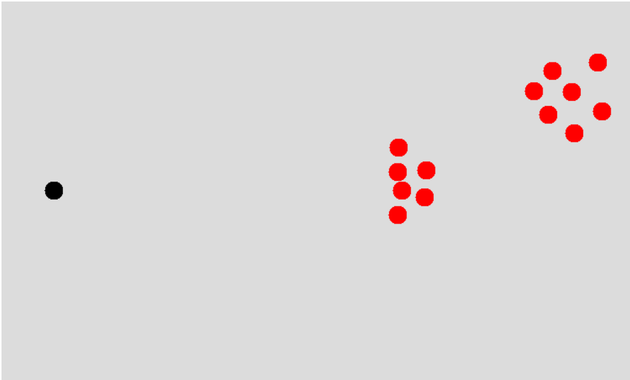
(d) Remaining Agents- Inconvenience

Figure 4.9: Experiment 2: Quantitative Analysis

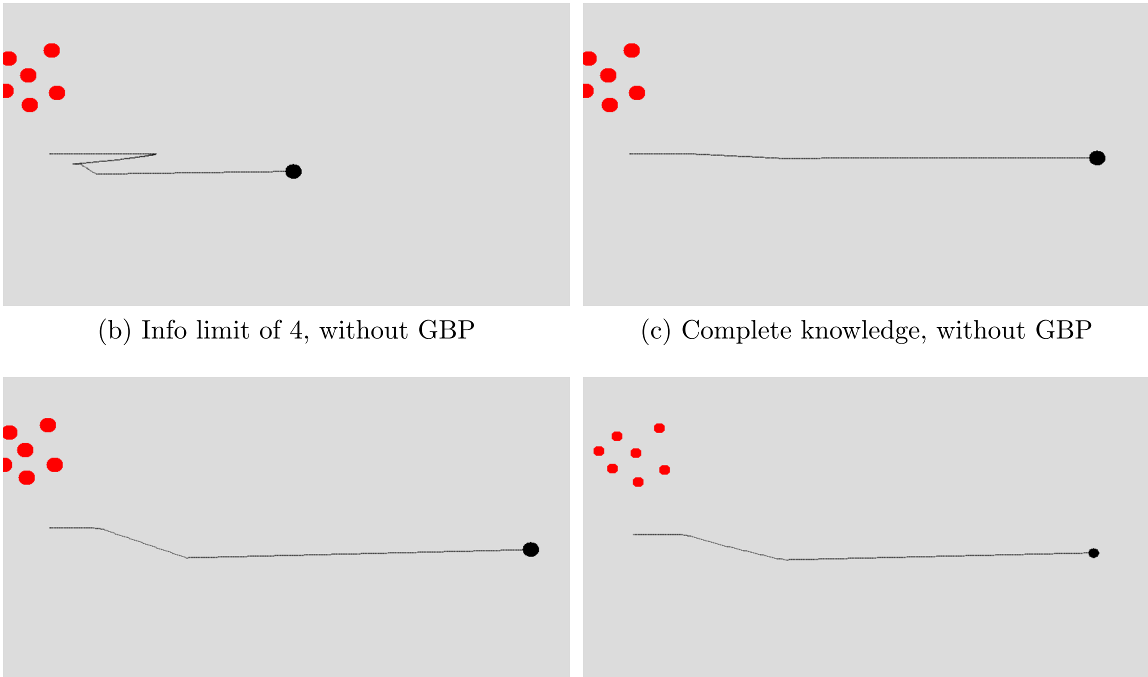
are exactly the same as for path III.

4.4.3 Filtering necessitates Group Based Perception

In Sects. 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 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).



(a) Initial Scenario



(b) Info limit of 4, without GBP

(c) Complete knowledge, without GBP

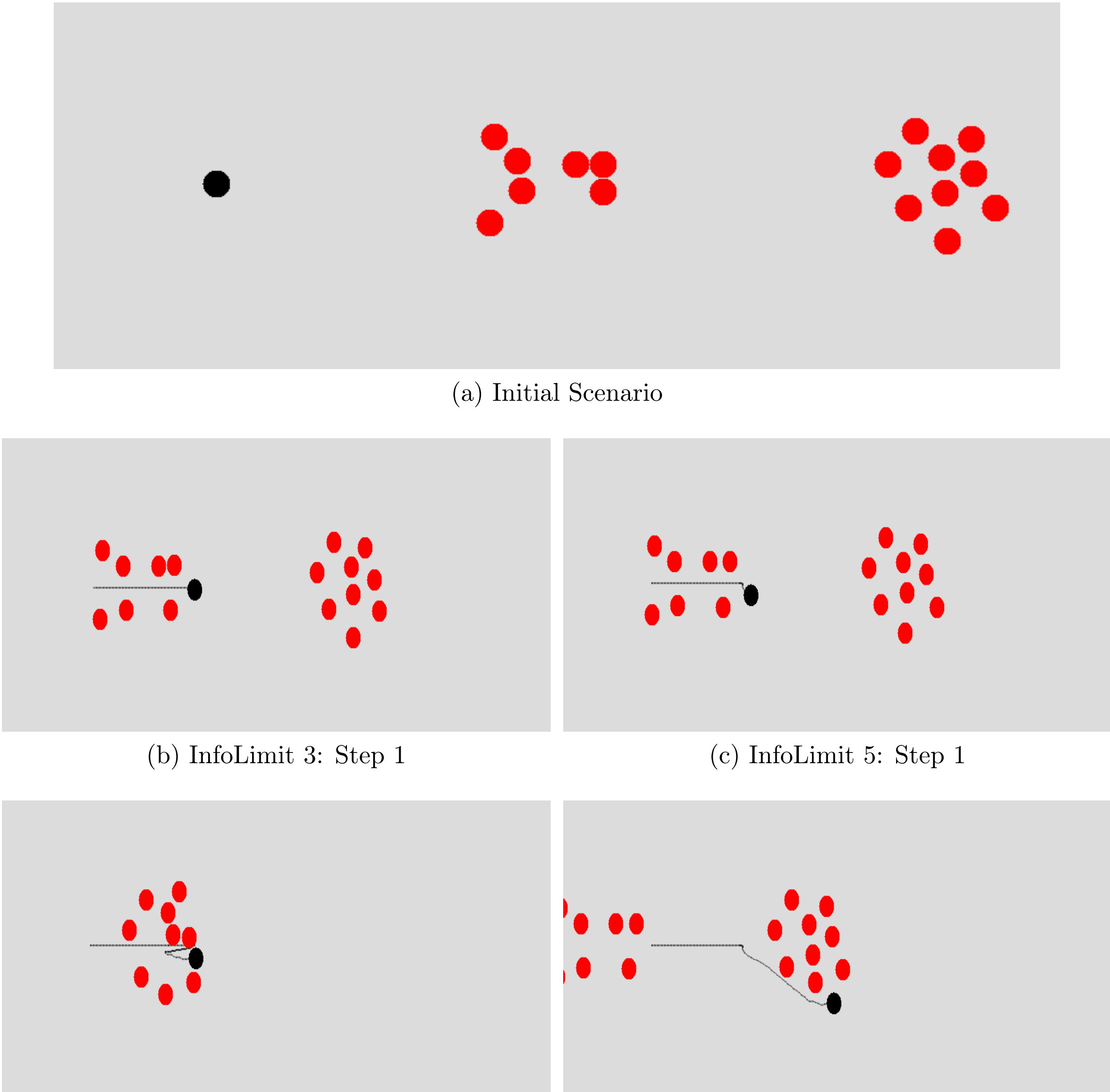
(d) Info limit of 1, with GBP

(e) Info limit of 4, with GBP

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

4.4.4 Effect of filtering of percept information

The final experiment (Fig. 5.3) 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 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



(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

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 [78] 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.

4.5 Summary and Future Work

In this chapter, the Information Based Perception model for agents which is based on perceived information rather than spatial distance has been introduced. The argument that this is a more appropriate model of human perception for crowd and egress simulation has been made. The behavior of this system has been illustrated through 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.

As mentioned earlier, for the IBEVAC model, the IBP model will have to be extended so that during filtering it can recognize cues that contain event and environment information and pass it to the appropriate modules for processing. Also, critical to the model is the quantification of information limits and appropriate definitions of interest; real world experiments will 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 the object, will also be the subject of these real world experiments. In emergency situations, according to Ozel [15], humans start perceiving cues in the environment differently. This idea was touched upon in the literature review chapter. The idea of modeling different cues and their effect on the agent's information processing capabilities as suggested by Kuligowski [19] is an idea that will be discussed in more detail in Chapter 7. As mentioned by Hill [83] there is also a reciprocal effect of cognition on perception where agents would turn towards objects of more interest. It is planned that this will also be incorporated into later version of the IBP model. The next chapter concludes this report by giving a brief description of the other parts in the model that have been considered so far and a more complete description of how the final IBEVAC model will look.

Chapter 5

Modelling Pre Evacuation Behavior in Agent Based Simulations Of Crowds

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 [31]. This uncertainty about the authenticity of the first sign of danger isn't an isolated incident [29, 30, 34]. 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 [30]. Modeling and simulation is one approach for analyzing and understanding egress behavior.

Software that simulates crowd egress is necessarily very complex because crowd egress from a building is itself a very complex system with lots of interacting elements (people, fire, alarms, etc.) each of which can cause different complications in the system. One of the most popular methods for studying and modeling complex systems is through Agent Based Models (ABM). In ABM, a set of heterogeneous, intelligent entities called agents are programmed with behavior approximating humans and placed in a partially observable environment. Asynchronous interactions between agents result in macro-level dynamics which can help observers learn more about the system.

Pre-evacuation uncertainty and investigation are features of human behavior during egress that are rarely considered in models. 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 [72] 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 [6, 9]. This variability is hard to model in existing models of pre-evacuation behavior. Also, during an evacuation people exchange event and environment related information with other evacuees. Evacuees are unlikely to follow blindly any and all messages 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 paper, we present one aspect of a behavioral model for Agent Based Modeling of crowd egress which we call the IBEVAC (Information Based Evacuation) model. This behavioral model models evacuees as information processing entities. More specifically, in this paper we introduce the information-based event identification and communication system that is used in IBEVAC. The evacuees identify and process information in terms of event cues which exist throughout the environment. 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. One large component of this complexity is the need to understand the behavior and decision making of the people taking part in it. 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 [10, 15, 29, 30]. 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 [15, 35, 52], 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 [10]. 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 [35], 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 [19] summarized the key findings of these studies and compiled a list of factors that influence pre-evacuation behavior. 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 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 [15, 30, 35] 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 6.1, there are very few existing models that take the pre-evacuation period into consideration. Pires [16] modeled the pre-evacuation decision making of an individual using a simple Bayesian Belief Network (BBN). França et al. [68] created a simulation model of the development of panic behavior during emergency egress. This model implemented the hysterical belief theory [4] 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 [72] 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.

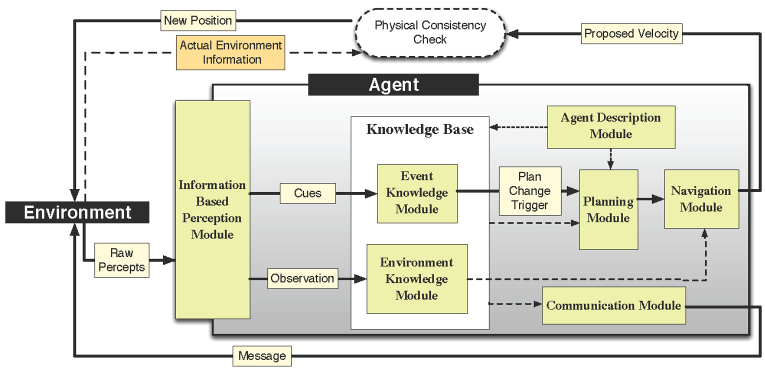


Figure 5.1: An illustrated representation of the IBEVAC agent architecture

5.3 The IBEVAC Model

This section gives an overview of the modular IBEVAC agent architecture. Figure 5.1 shows this architecture. There are many objects or actions that an agent can sense or observe in the environment. We call these *raw percepts*. According to their sources, they can be classified as *observations* from the environment and *messages* from other agents. The Information Based Perception (IBP) Module is the only gateway through which the agent receives information from the environment. This module is explained in more detail in [96]. The IBP Module passes a percept to the Knowledge Base.

The *Environment Knowledge Module* stores a representation of the layout of the environment that is formed as a result of the observations of the agent. Information regarding accessibility of links is also stored. As a detailed discussion of this module is beyond the scope of this paper, all agents are assumed to have complete knowledge of the layout. However, agents can learn about inaccessible links only through direct observation or through messages from other agents. The *Event Knowledge Module* is the focus of research in this paper. It stores the agent's beliefs about the current state of the environment. Cue perception alters these beliefs and triggers a state change in the agent which is then handled by the Planning Module. This Module is explained in more detail in section 5.4.

The intrinsic characteristics of the agent like the agent's size, speed, mass and social role are stored in the *Agent Description Module (ADM)*. It is also responsible for determining the strategies and actions taken by the Planning Module and in determining the effects of the cues on the Event Knowledge Module (Section 5.4). The *Planning Module* stores the current state of the agent i.e. whether it is exploring, milling or escaping and creates a plan of action for the agent as a set of goals. Each goal is a location that is passed to the Navigation Module. 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, for milling behavior the agent gathers with other agents at the nearest *corridor* (See Figure 5.2) and during escape the agent heads towards the nearest exit.

Communication between agents is facilitated by the *Communication*

Module. It transmits messages to agents within a communication range. The working of this communication is explained in more detail in Section 5.4. The *Navigation Module* uses a four level navigation system. 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 level determines a possible collision free path to the farthest visible spatial way point. Finally, a physics engine ensures that objects don't pass through other objects.

5.4 Event Identification and Pre-evacuation behavior

It is known that the ambiguity, source and consistency of the cue [10, 30, 52] are the key factors (Section 5.2.1) 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.

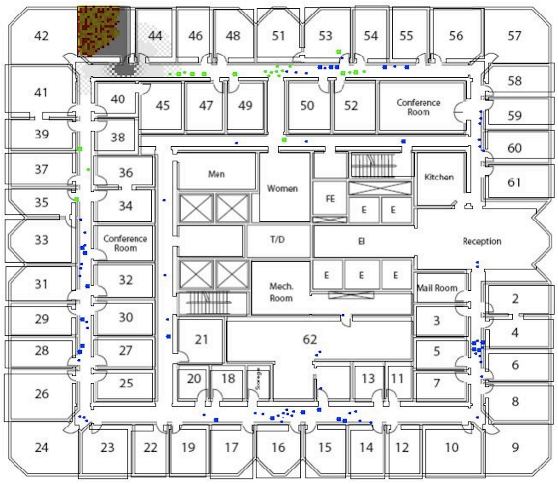


Figure 5.2: First of two floors from World Trade Center, California. Fire is started in the corner room and generates smoke. Fire kills agents. Smoke depending on concentrations slow or kill agents. The longer rectangles are corridors connecting rooms and the open area on the right center is the exit.

5.5 Results

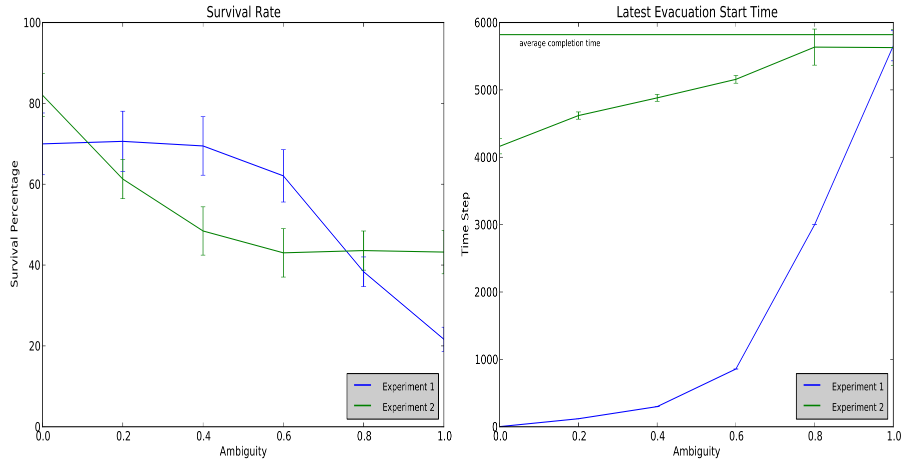
Experiments were conducted using IBEVAC to demonstrate the effect that cue perception and communication can have on egress. Both experiments were conducted on the two floor office environment shown in Figure 5.2. Simulations were conducted with 200 agents randomly distributed all over the environment and data was collected after averaging over 100 replications of the simulation.

5.5.1 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 5.3a show the error plot of the survival percentage and the one in Figure 5.3b 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.

5.5.2 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 5.3: Observations from 100 replications of each setting of the IBEVAC Simulation

The green curves in Figure 5.3a and Figure 5.3b 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 5.3b 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.

5.6 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 [97–99] 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 [100], 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 [101], 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 [102] 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 [103, 104] 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 [105] or if the wayfinders are under stress or time pressure [15]. 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 [105].

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 [106]. 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* [107]. 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 [108] 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 [109] 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 [110] 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 [111] 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 [112]. 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 [113] 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 [114] 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. [115] confirmed the findings about familiarity and visual access. Evans et al. [116] discovered that distinct wall colors reduced wall finding complexity. Thorndyke [117] found out that experience does improve way-finding but over the period of months rather than hours.

According to [118], 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. [112] explored the various strategies that people use in exploring multi-storey buildings. The first strategy shown by Kuipers et al. [119] 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 [120] 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. [121] 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 [122]. 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 [123] 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 [124] 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 [125] 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.

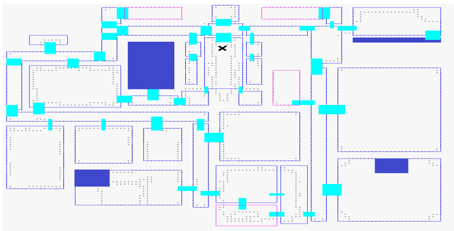
Most experiments tried to constrain the first part of knowledge acquisition. A typical example is Melinger Knauff and Bulthoff [104] who ensured that all particiapnts got indentical stimuli in order to be able to fairly compare secondary task comparison. So participants watched a video rather than actively 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 [126]. 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.

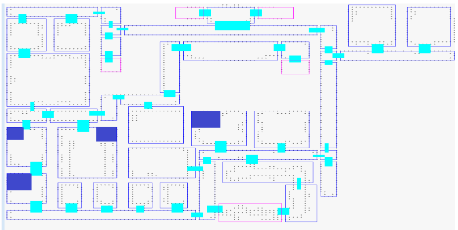
The next phase, which we call *knowledge testing phase*, starts when the eleventh prisoner has been freed. During the phase, the cognitive map formed by the player is tested through a series of three tasks. By not revealing the nature of the second phase to the player at the beginning of the game and 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* [105].

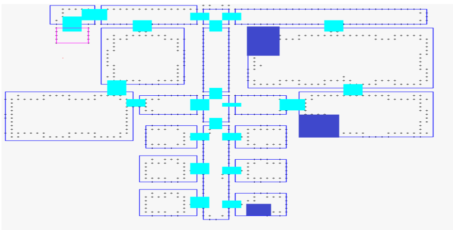
Once the player locates and presses the switch that is revealed in this room, the player is given instructions to the second floor library. There are two important factors for having this particular location. Firstly, the library has four entrances and is very likely that the player would have entered 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* [105].

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

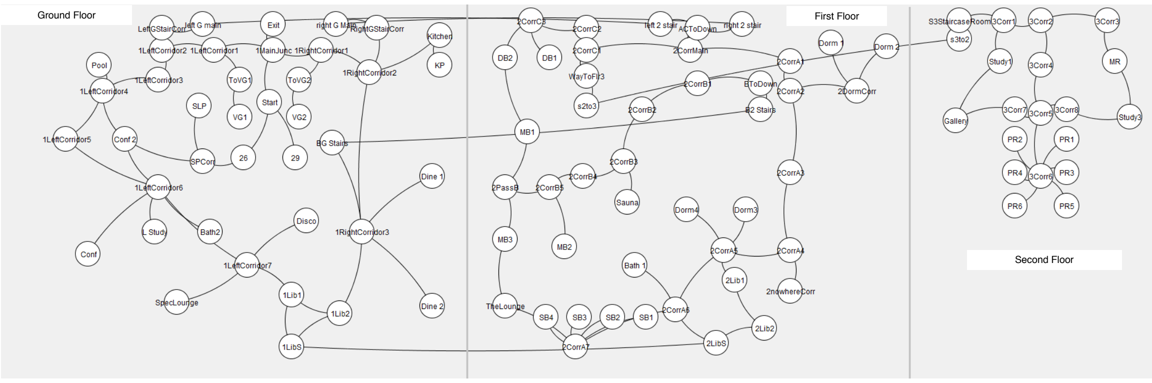


Figure 6.2: Room Layout Graph

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 $y_r \times (unscaled\ diameter)$.

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.

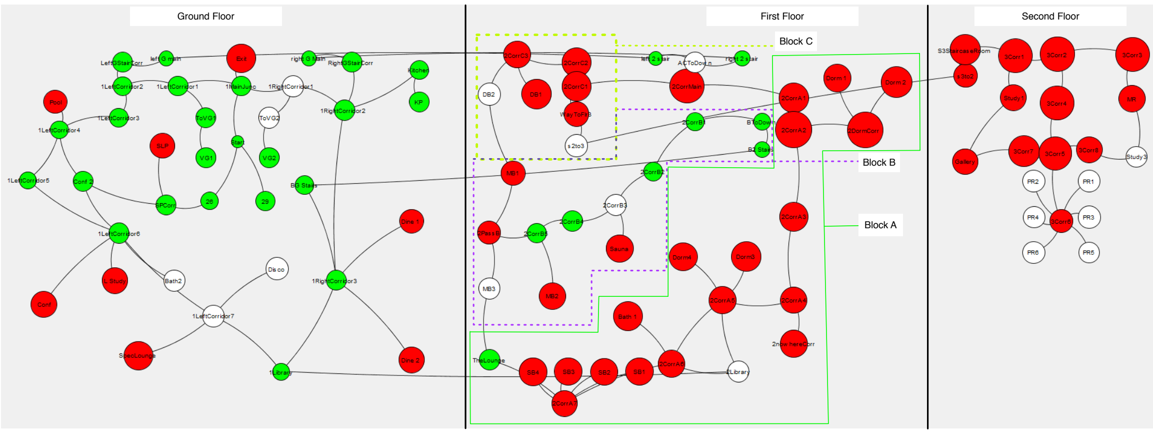


Figure 6.3: Map scaled by normalized number of visits

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 [112] 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).

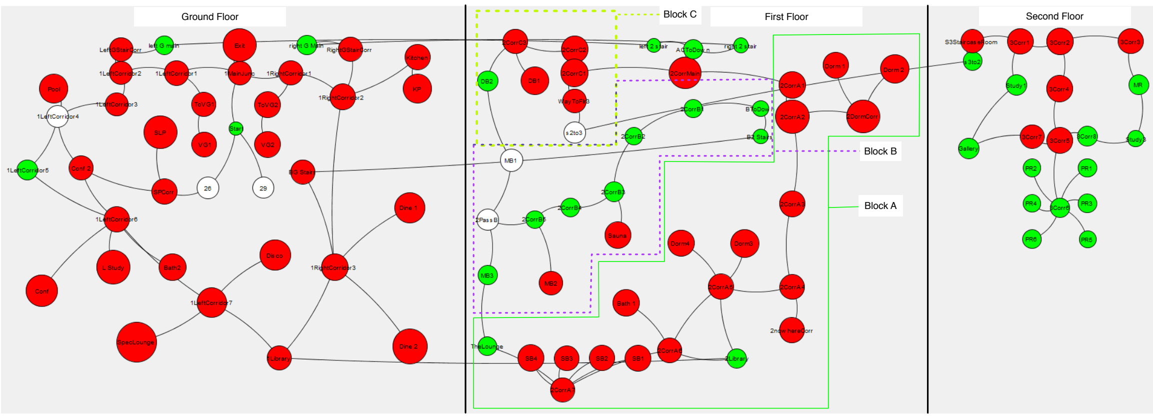


Figure 6.4: Map scaled by floor normalized number of visits

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_{ab}^n:

$$p_{ab}^{n} = \frac{\left|P_{ab}^{(n,D)}\right|}{\sum\limits_{x \in R} \left|P_{ax}^{(n,D)}\right|} \tag{6.5}$$

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.

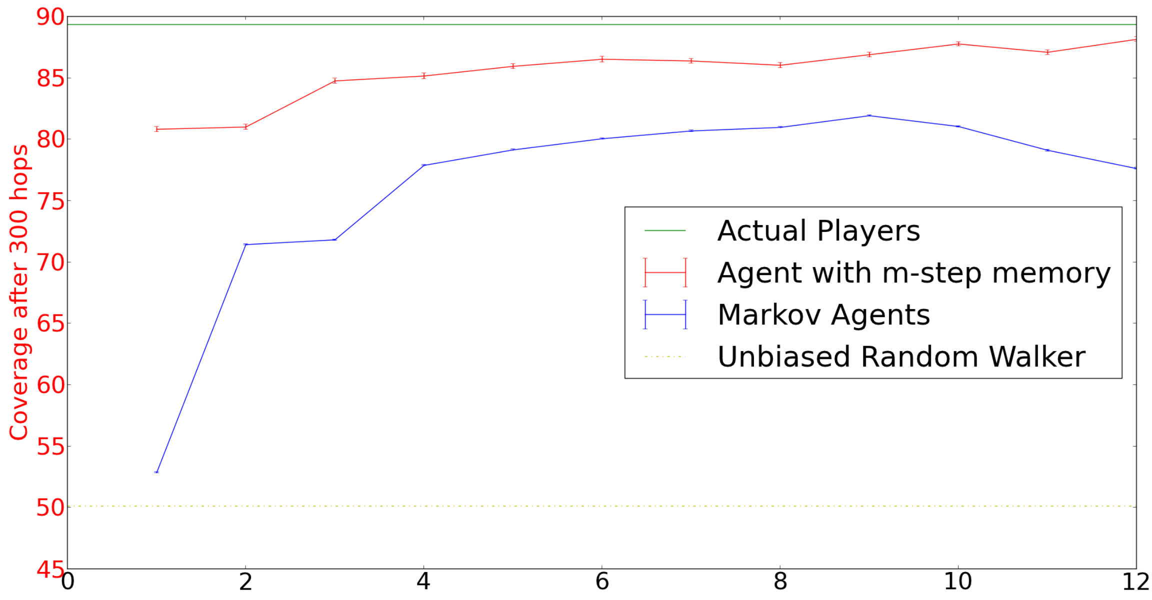


Figure 6.5: Coverage for 300 hops

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.

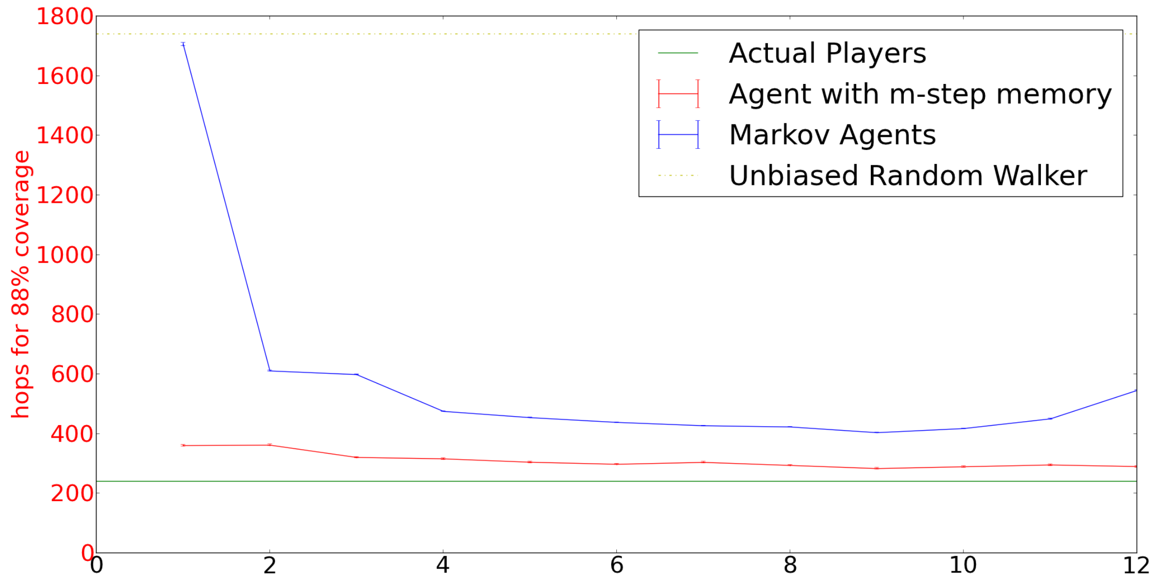
6.5.4 Empirical Analysis

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.

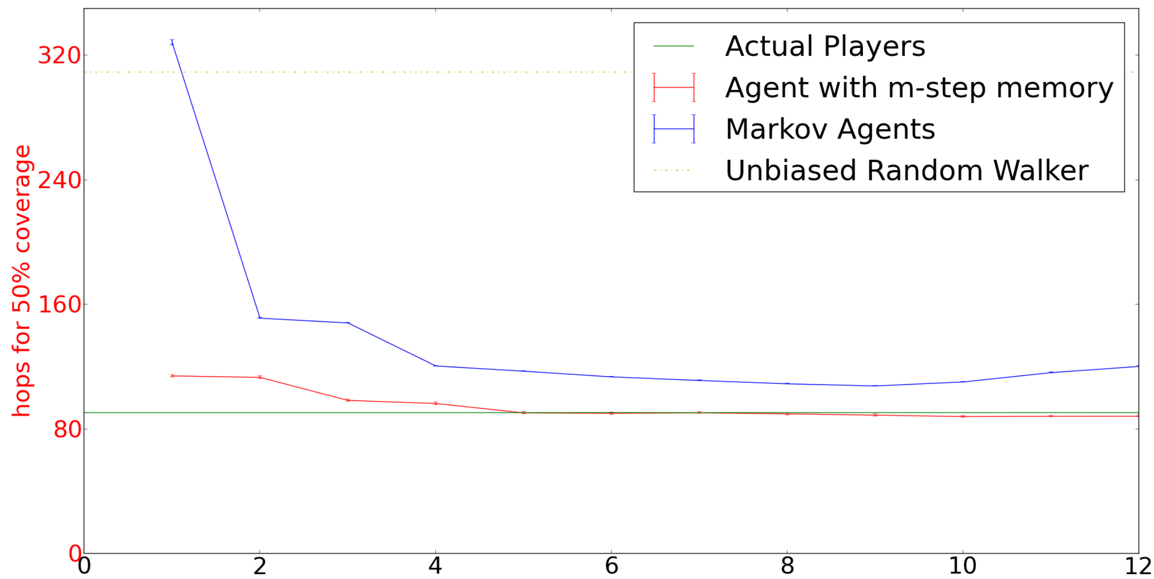
6.5.4.1 Existence of decision points

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

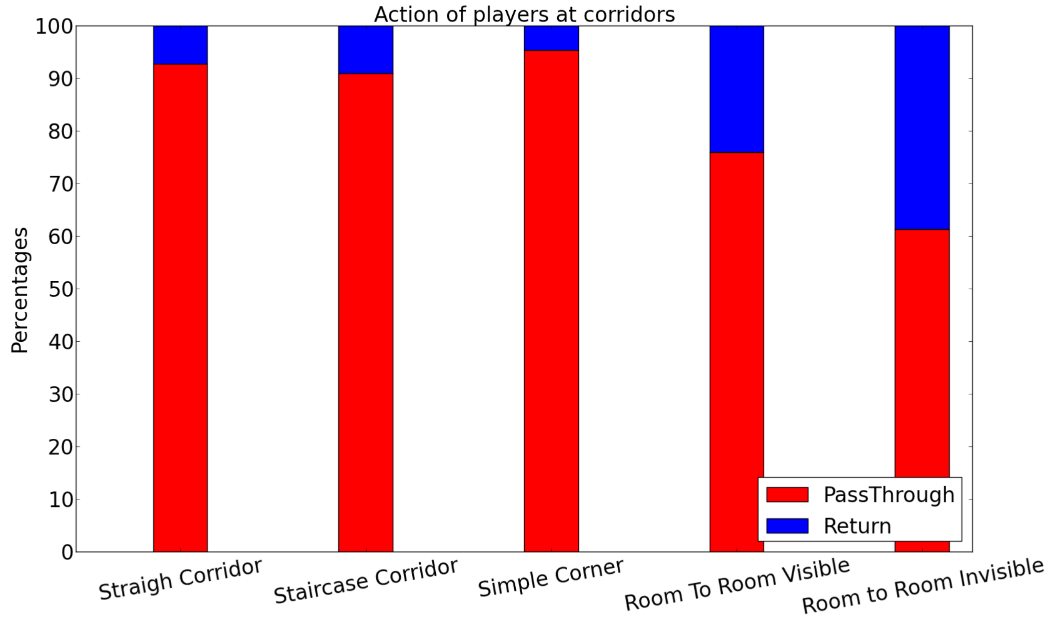


Figure 6.7: Behavior at simple corridors. There are definite decision points during exploration

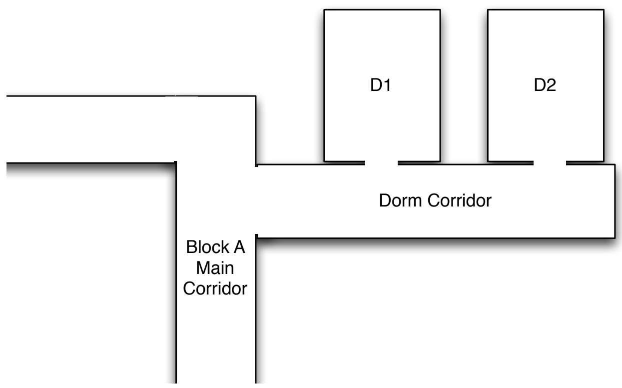


Figure 6.8: Layout of the relevant corridor

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-

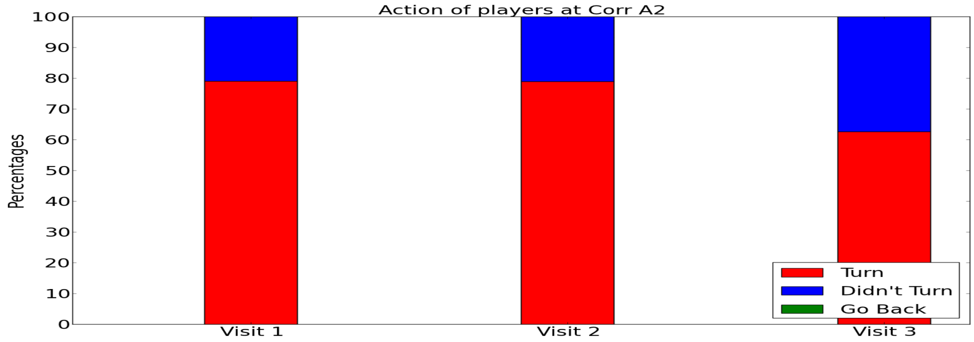


Figure 6.9: Behavior at *junction A2* during tasks

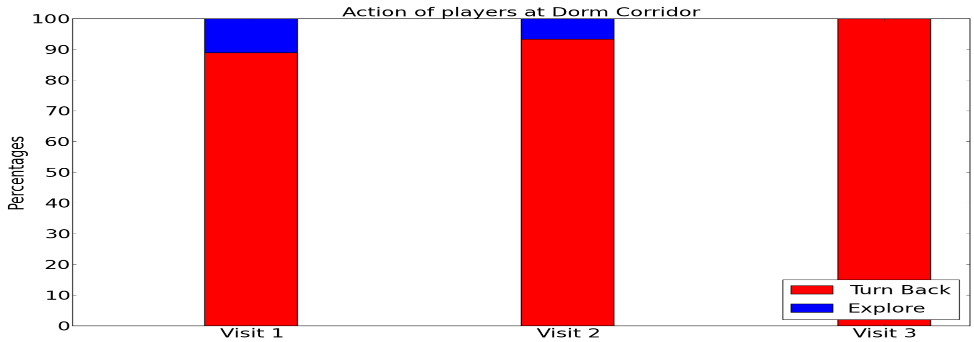


Figure 6.10: Behavior at *Dorm Corridor* during tasks

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 [108].

Chapter 7

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. 7.2.1, an expected time frame for finalizing the design details of the model is first discussed. Following this, in Sect. 7.2.2, 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. 7.2.3. However, before the future work and plan of action is discussed, Sect. 7.1 first summarizes and concludes the report.

7.1 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. 7.2.

7.2 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. 7.2 at the end of this chapter.

7.2.1 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. 7.2.2 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 7.1: 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

7.2.2 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 7.2.2.3 then presents an estimated time-frame for completion of different implementation related tasks.

7.2.2.1 The MASON frameworok

The IBEVAC model is implemented in Java using the MASON framework [127]. 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.

7.2.2.2 DEPATHSS

DEPATHSS is a simulation system for symbiotic simulations of evacuation scenarios (Screenshot in Fig. 7.1). It is not directly related to the IBEVAC model. However, the Java based implementation of the simulation system provided a good starting point for

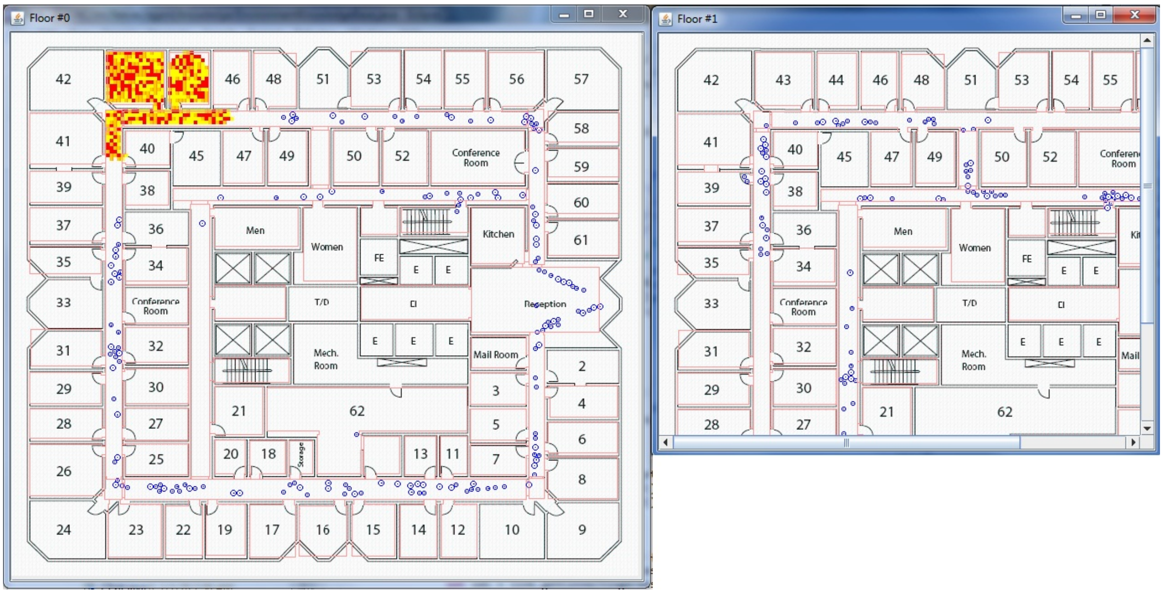


Figure 7.1: This figure shows a screenshot of the evacuation simulation using DEPATHSS of a 2-floor office building with fire propogation modelled (The red, yellow and orange color at the top left of the screen on the first floor). Agents are in blue.

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 7.2: 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

7.2.2.3 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. 7.2.2.1 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.

7.2.3 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 [89, 91, 128] use the presence or absence of certain characteristics of motion like *reciprocal dances* [89, 128] 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. [129], 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 [130, 131]. 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 [4, 6, 34, 38] 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 [132].

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 [133], 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 [134] and RVO2 [91] 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.

7.2.3.1 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 7.3: 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.

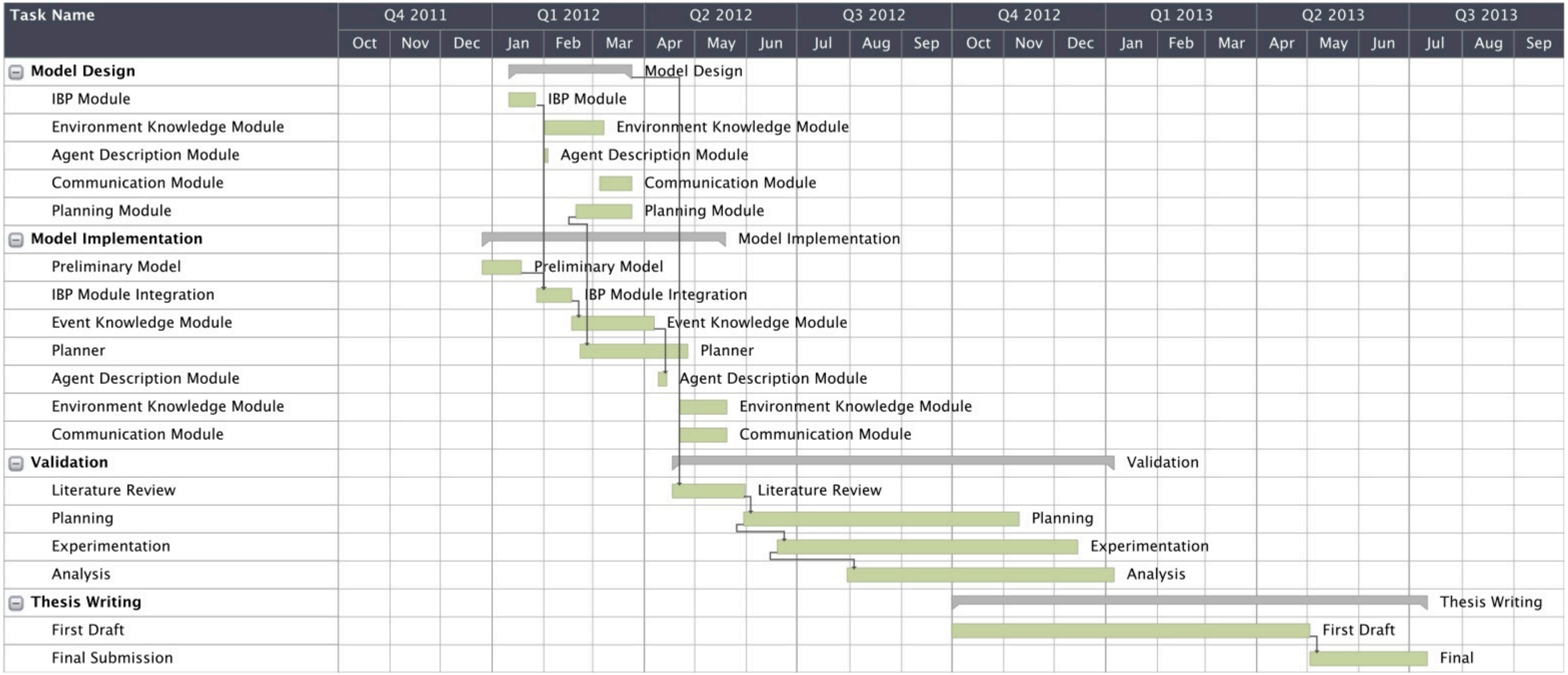


Figure 7.2: Gantt Chart showing the plan of action for the present thesis. The chart excludes weekends, public holidays and 21 days a year from the calender to account for allowed leave.

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.

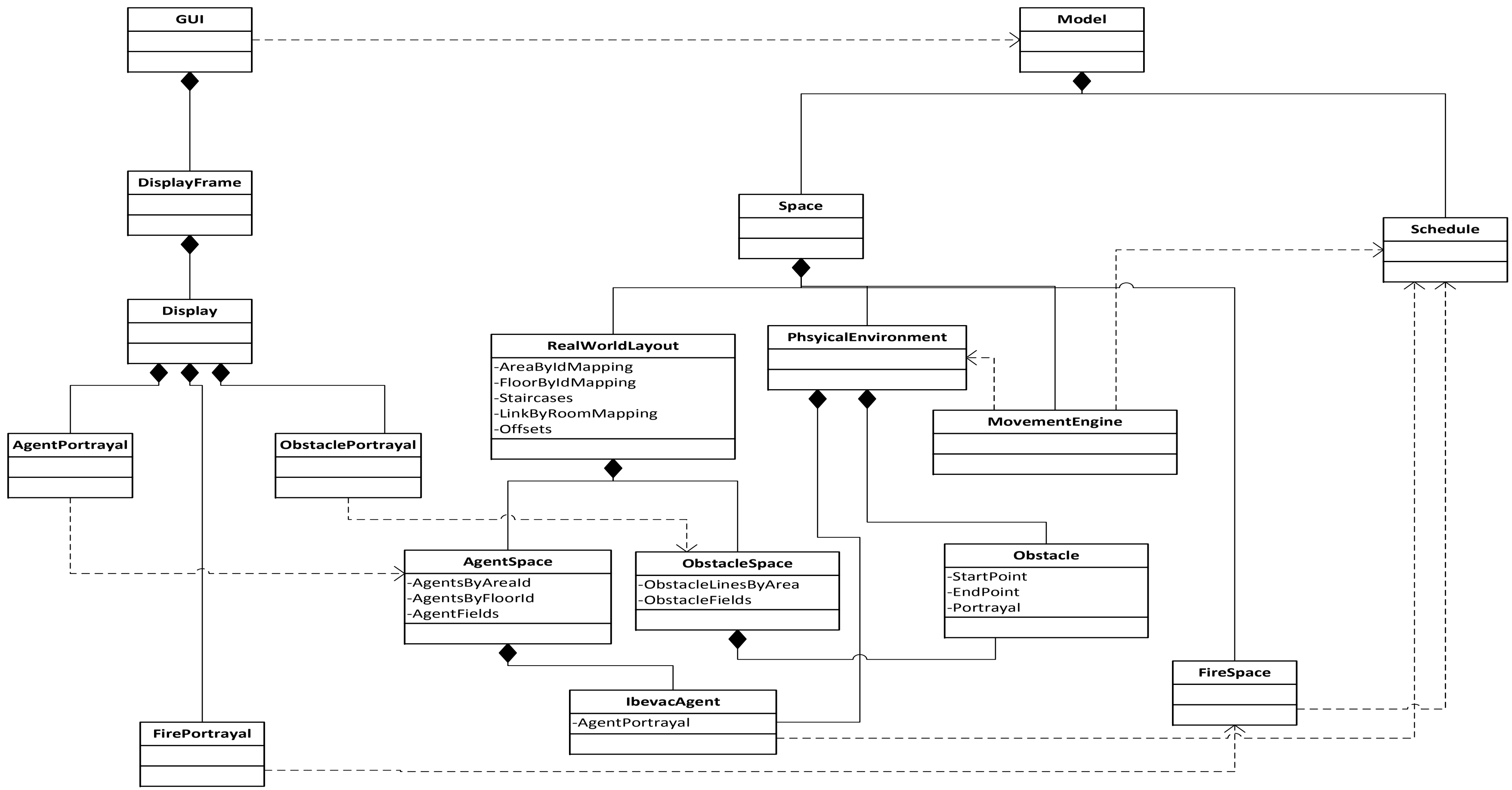


Figure A.1: Class Diagram shows the overall class structure of the model

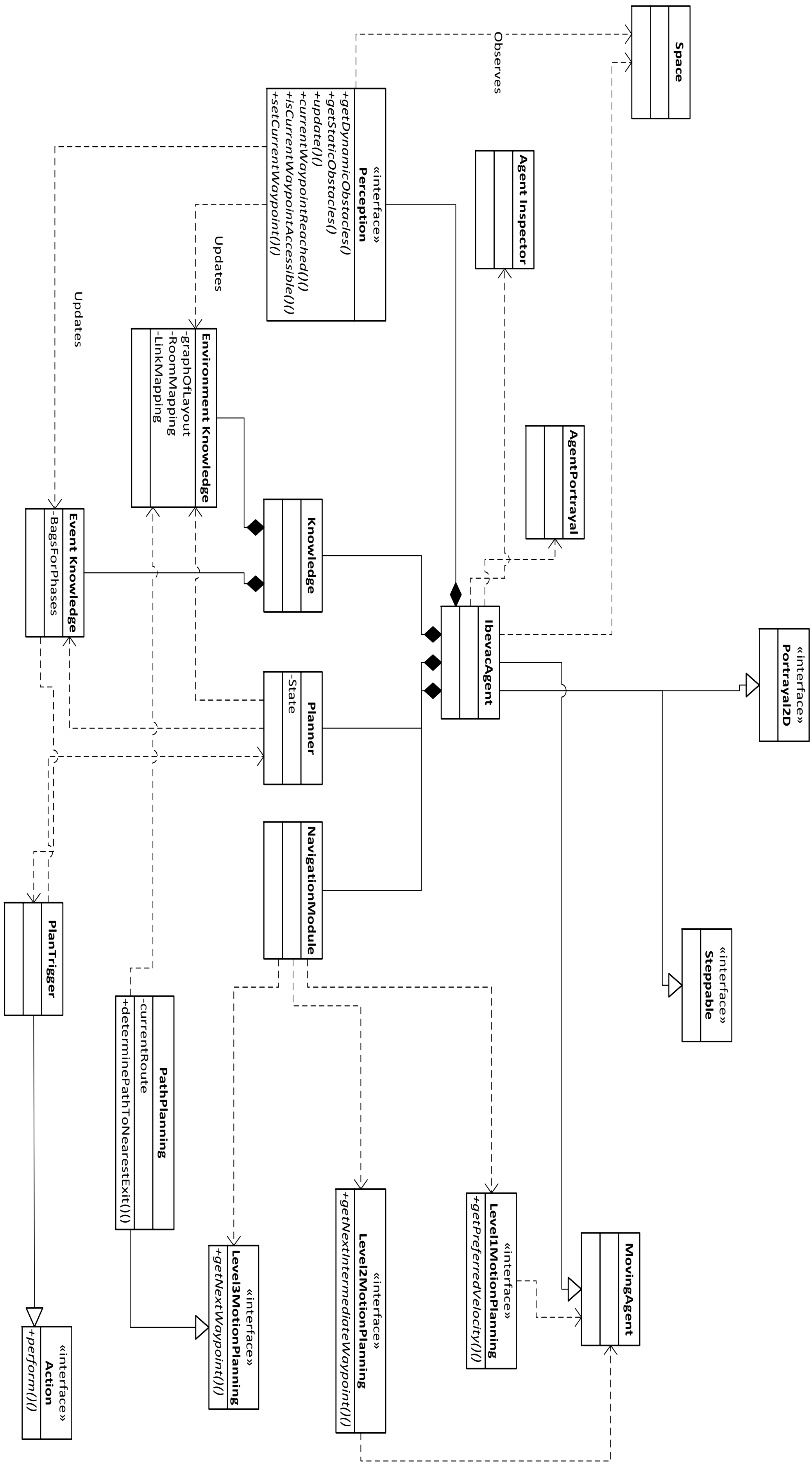


Figure A.2: This Class Diagram shows the agent class in detail

Appendix B

Validity check for Markov analysis

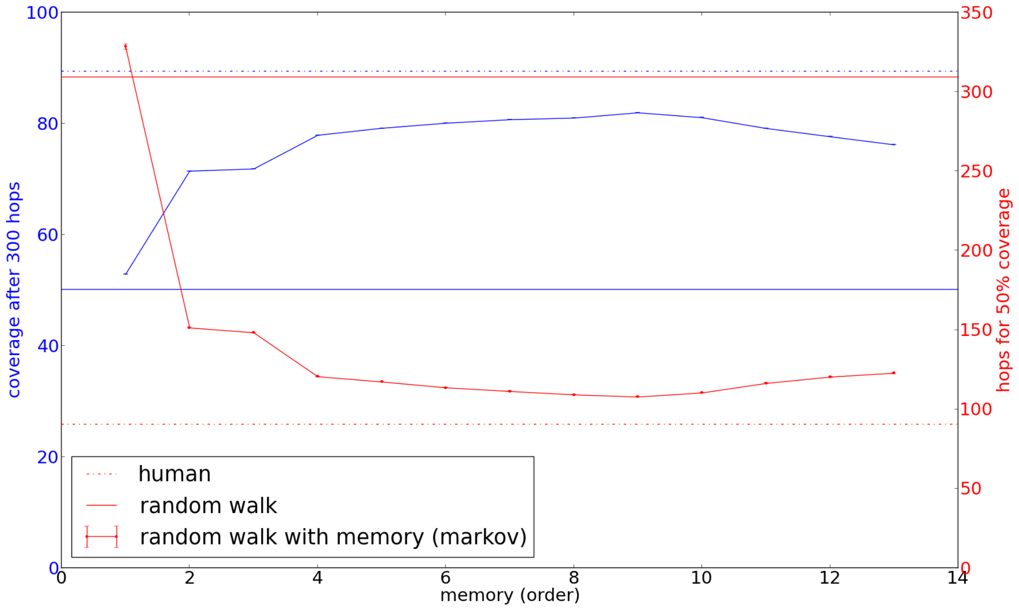
B.0.4 Effect of dataset size

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.

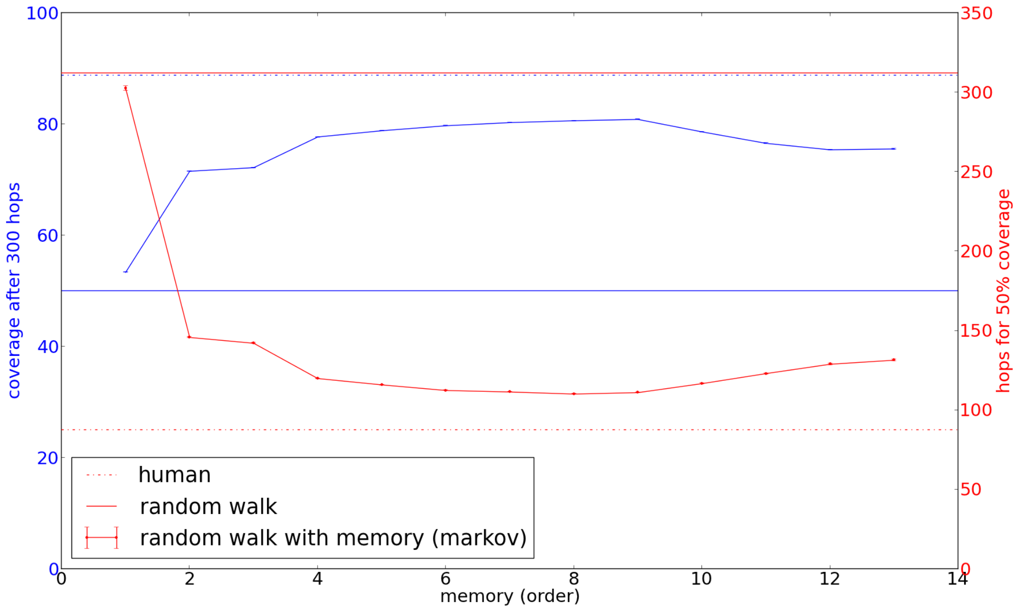
B.0.5 Decision base size at decision points

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

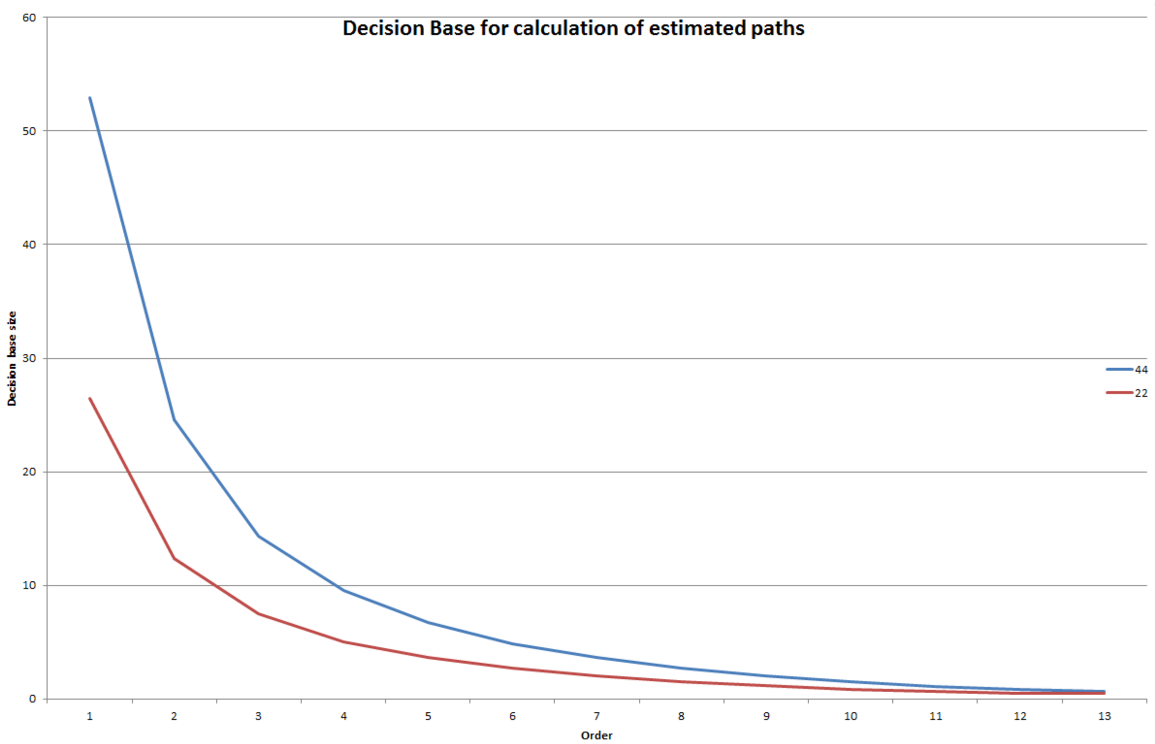


Figure B.2: Comparison of the decision bases

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