Social Spatial Behavior for 3D Virtual Characters

by

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Abstract

This thesis presents a social navigation solution for virtual game characters, capable of generating sensible human-like spatial behavior in social scenarios. In a social setting with several groups of virtual characters, our model generates group-joining, group-leaving and group-revisiting behaviors for an individual character. We consider interest as the main motivation behind character's interactions with the groups. Thus, our social navigation model not only navigates the character toward interesting groups, but also continuously evaluates interestingness of groups and utilizes it to build group-leaving and group-revisiting mechanisms. In an engineering approach, we use the psychological knowledge on social spatial behavior to produce an internal representation of interest; then combine it with existing social navigation models to build our solution. We describe the two-stage implementation of our model, consisting of planning and realization of social spatial behavior. Finally we present simulation results of four testcase scenarios as proofs of concept for our model.

Keywords: Social spatial behavior generation; social navigation model; 3D human-like virtual character simulation for games

To future Nahid,

to never forget if it is not fine,

it is not the end yet.

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This really is the end; and I have come a very long way to this finish line. It wouldn't be possible for me to be here if it wasn't for the help and support of a few wonderful people that I would like to thank here. I hope they accept my sincerest appreciation, despite all the grammatical errors, typos and Nahid-made words; after all, this section has not been proof read.

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Nahid Karimaghalou
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Table of Contents

List of Figures

List of Equations

1. Introduction

1.1. Motivation

Human-like virtual characters, shortly referred to as *virtual humans*, have injected life to the gaming and entertainment industry and turned social virtual environments into a widely popular reality. A remarkable example application of these virtual humans is Second Life (Linden Lab, 2003) which is an online virtual world developed by Linden Lab in 2003. Second Life provides its users an environment to interact with one another through avatars that are embodied virtual representations of the users. These interactions come in a variety of forms such as exploring the virtual world, socializing and participating in individual or group activities. According to an official infographic by Linden Lab released for the tenth anniversary of Second Life in 2013, the game now has 36 million registered users, a million monthly active users and over 400,000 new accounts per month (Linden Lab, 2013).

There is a massive research effort to augment the virtual human models with different levels of autonomy and turn them from fully scripted characters into virtual humans capable of performing complex un-authored behaviors in dynamic virtual environments. The ambitious vision of such researchers is to build virtual humans that are capable of fully perceiving their environment, interacting in a natural way with humans or other virtual humans using human-like means of verbal and non-verbal communication, having internal models for desires and intentions and exhibiting affective qualities such as emotions (Swartout, 2010). A fundamental behavior to be autonomously generated in this regard is spatial behavior in the social virtual environment which we refer to as *social spatial behavior*. Social spatial behavior not only provides access to the environment and clusters of other individuals for the virtual character, it is also a way of non-verbally communicating desires and intentions through whole-body movements. Related computer science and Human Computer Interaction (HCI) studies referred to social spatial behavior as *social navigation* and defined it as the process in which perceived social factors and rules influence navigation and steering behavior (Riedl, 2001).

Social navigation research is based on the realization that an individual character's spatial behavior in a social setting is influenced by the environment dynamics, other individuals' attributes and attributes of collective groups of individuals in the environment. These influences are then modeled and utilized as driving forces that navigate the virtual character toward their source. As an example, Pedica and Vilhjálmsson (2008) proposed a steering model for navigating a virtual character toward a conversational group in the social virtual environment. They assumed participating in conversations is the motivation that attracts the virtual character to join a group. Based on this motivation, they proposed a simple distance-based group selection process and defined three distance-based social behaviors that are the driving forces behind their steering model.

There are two major limitations to these models: first, they consider an unrealistic motivation for group selection e.g. closer distance to groups; and second, there is little to no traces of a temporally large-scale social scenario present in them. A temporally large-scale scenario is one that happens over a longer period of time, compared to the time it takes for the character to join a group. Similar to Pedica and Vilhjálmsson (2008) many other researches on social navigation models focus on planning one instance of movement toward a single optimal position that is often selected based on closer distance, and then steer the character toward that position. Whereas in real-life social scenarios, the motivational values for optimal position selection are more complex and dynamically changing; thus, humans are required to make a series of movements toward several locations, each of which is the optimal position at a certain point in time.

Limitations of these social navigation models prevent them from generating human-like spatial behavior in temporally large scale social scenarios. We believe that to be able to effectively generate human-like spatial behavior in such scenarios, a social navigation model should have an internal dynamic system of representing social motivations for group selection. This system can be employed to plan not only the optimal position in a group at any time, but also the time to leave a once-optimal position for the next group. This mechanism of group-leaving behavior generation makes social spatial behavior more human-like in a temporally large scale social scenario. In a social setting with several conversational groups, such a model needs to be capable of answering the following questions: What is a more realistic social motivation for a virtual human to join a group? How does this motivation change over time? How does a virtual human join a group? When is the appropriate time for the virtual human to leave a group? And finally, how does a virtual human revisit groups based on the changing motivations?

In this thesis, we build a social navigation model that addresses the above questions. In addition to group-joining behavior, our model offers mechanisms for generating group-leaving and group-revisiting behaviors for the virtual character. These behaviors enable our model to generate human-like social spatial behavior in temporally large scale social scenarios and that differentiates us from other existing models in the literature. Figure 1.1 gives the reader an example of the virtual social setting in which our model performs the social navigation, while Figure 1.2 provides a high level abstraction of the cycle of actions that result in human-like spatial behavior over a long period of time. In the next section we provide an overview of our thesis work.

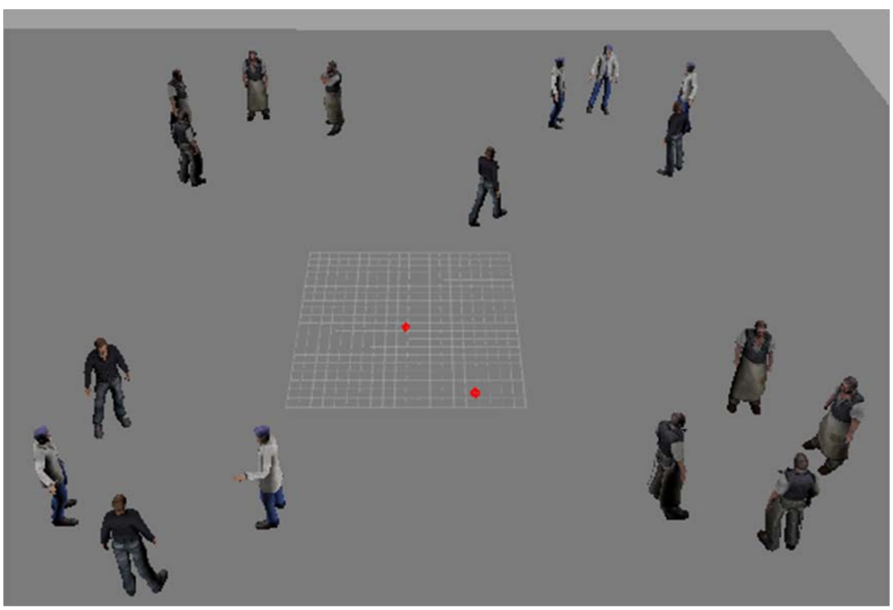


Figure 1.1. An example of the virtual social setting in which our model performs the social navigation.

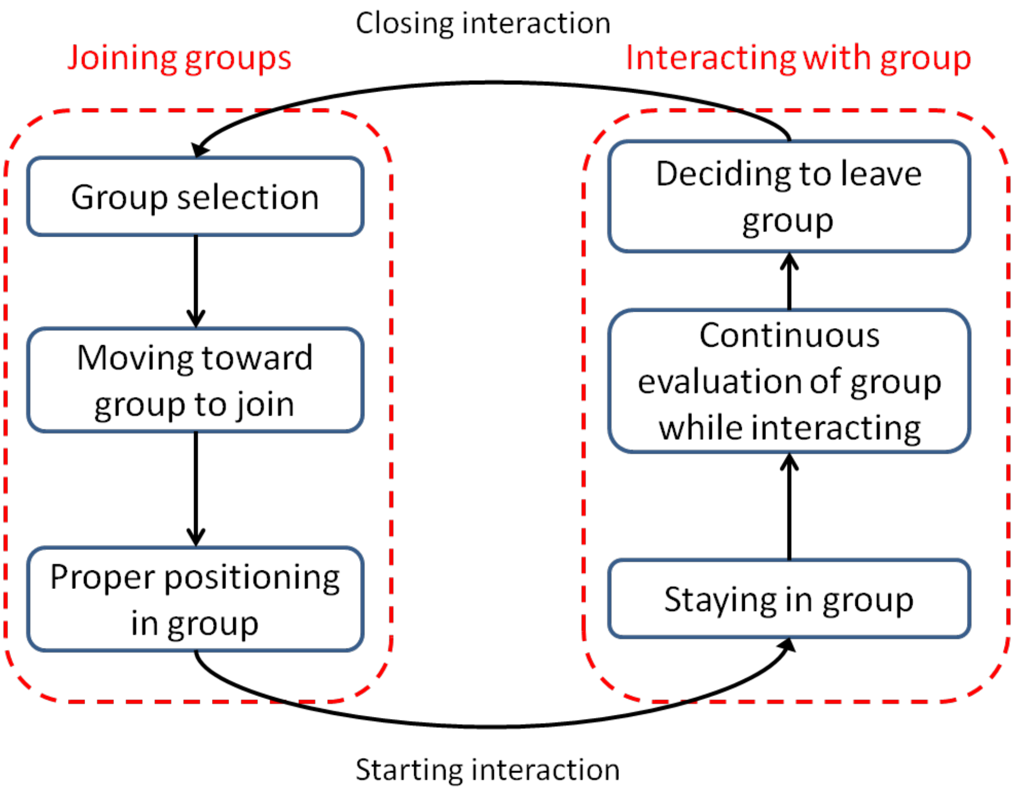


Figure 1.2. ***A high level abstract view of the cycle of actions that results in human-like social spatial behavior in a temporally large scale social scenario***

1.2. Overview of Thesis Work

This thesis presents a social navigation solution for human-like virtual characters that is capable of generating human-like spatial behavior in a temporally large scale social scenario. The scenario is a social setting with several groups of virtual humans, and our goal for the model is to generate group-joining, group-leaving and group-revisiting behaviors for a subject character in this setting over a long period of time. We consider *interest* as the main motivation behind a subject's selection of groups for interaction and we compute *interestingness* based on static and dynamic properties of group members. Our social navigation model is capable of not only navigating the subject toward *interesting* groups, it is also continuously evaluating *interestingness* of groups and utilizing it as a group-leaving and group revisiting mechanism.

We combine our psychological knowledge of spatial behavior with existing social navigation models to build this model. In the limited scope of two virtual characters regulating their distance, we benefit from existing psychological studies and theories to generate human-like behavior. However, there is a lack of psychological data on spatial behavior in the larger scale social settings and over longer periods of time. Therefore, we employ an engineering approach to define a dynamic representation of interest and then use it as the non-existent psychometric function that drives human-like spatial behavior in large scale settings.

Additionally, we present a two-stage implementation of our solution that plans the spatial behaviors using our model and then realizes it in real-time through the SmartBody real-time 3D animation software (Thiebaux, Marsella, Marshall & Kallmann, 2008) developed in University of Southern California[1]. This implementation is used to simulate sample testcase scenarios as a proof of concept for our model and the results of these simulations are also provided. Lastly, we offer public access to all our source codes and resources through http://ivizlab.sfu.ca/research/SocialCharacterThesis/ so that further evaluations and studies can be performed on our model.

Below is a detailed summary of my main contributions in this thesis:

- Improvement and further development of an existing social navigation model so that the generated behaviors are planned rather than reactive
- Building a social navigation model capable of generating human-like social grouping behavior for non-player characters in stationary to semi-stationary social game scenes
- Building group-leaving and group-revisiting mechanisms into our social navigation model that results in more human-like behavior in temporally large scale social scenarios.
- Employing interest as virtual character's motivation for action selection
- Providing a dynamic representation of interest based on the behavior regulating mechanisms of habituation and boredom in humans, using an engineering approach
- Implementing our proposed social navigation model in a two-stage behavior generation process using SmartBody software

[1] Available online at: http://smartbody.ict.usc.edu/

- Implementing a testcase designer tool to facilitate design and effective maintenance of testcases
- Simulating several testcases as proof of concept for our model

1.3. Thesis Organization

In this chapter we described our motivation for addressing the social spatial behavior generation challenge and provided the reader with an overview of our thesis work. The rest of this thesis is organized as follows: in Chapter 2 we perform a literature review of the relevant social psychological models of spatial behavior, as well as navigation and steering models available in spatial behavior generating systems. Chapter 3 presents a step-by-step explanation of our proposed social navigation model. Chapter 4 describes the details of our two-stage implementation of this model. Chapter 5 demonstrates the effectiveness of our system through four testcase scenarios executed using our implementation and discusses the results. Finally Chapter 6 draws the conclusion and suggests several areas for continuation of this work into the future.

2. Related Works

2.1. Overview

In this chapter, we provide the reader with brief literature reviews on two important domains which contributed to our work: psychological information on social spatial behavior, and existing models of generating social spatial behavior for virtual characters. In the first part, we provide an overview of psychological studies and theories on social spatial behavior of humans. This is essential to building our social navigation model because these psychological models serve as the reference implementation for it. Also, there are existing social navigation models that partially realize our vision for this model. We study these models in order to find a state-of-the-art social spatial behavior generation system that can be employed as the baseline for our solution.

2.2. Psychological Theories about Social Spatial Behavior

This section presents an overview of the psychological theories about social spatial behavior of humans to be used as the reference implementation for us. We start with the studies and theories that specify attributes of human spatial behavior in smaller scale of a dyadic social interaction, and then move to larger scale spatial interactions with one or more groups. Lastly, we describe two behavior regulating psychological concepts that help us build the internal model of interest for our social navigation solution.

2.2.1. Dyadic Spatial Interactions

A large body of work on small scale spatial behaviors of humans is dedicated to interpersonal distance regulation between two interacting individuals. Equilibrium theory of nonverbal intimacy (Argyle & Dean, 1965) is an example of these theories. This theory, as cited by Bailenson, Blascovich, Beall and Loomis (2003), describes the inverse relationship between mutual gaze and interpersonal distance in dyadic interactions. According to the equilibrium theory, mutual gaze is a cue signaling intimacy between two individuals and if considered inappropriate by the individuals, they increase their interpersonal distance to convey less intimacy.

A substantiation of this theory is presented in an empirical study (Patterson, 1977). This study shows that the level of intimacy of the two individuals interacting with each other is the key factor that regulates and maintains their affiliative behaviors such as interpersonal distance, body orientation and eye contact. In a one to one seated interview scenario, Patterson manipulated the seating distance of interviewer and interviewee, and found out that a too close distance (relative to what interviewee considers comfortable distance) results in reduction of eye contact and a less direct body orientation.

Proxemics theory (Hall, 1966) is another psychological theory that suggests a spatial structure in interactions between two participants. Hall claims that there are four areas, called *reaction bubbles*, around each individual interacting with another individual; these bubbles are labeled intimate, personal, social and public areas from smallest to largest. Based on the intimacy level of the two interaction partners, interaction takes place in one of these areas. The radius of intimate area is from 0 to 40-50 centimeters and body contact is allowed here. Normally, couples or parents and children interact in their intimate areas. Personal area ranges from 40-50 centimeters to 150 centimeters and contains interactions of close friends. The social area on the other hand is where interactions with acquaintances or strangers happen and ranges from 150 to 300 centimeters. Finally, any distance above 300 centimeters is considered public area, which is for audiences or public speaking (Was, Gudowski & Matuszyk, 2006). Figure 2.1 depicts these reaction bubbles.

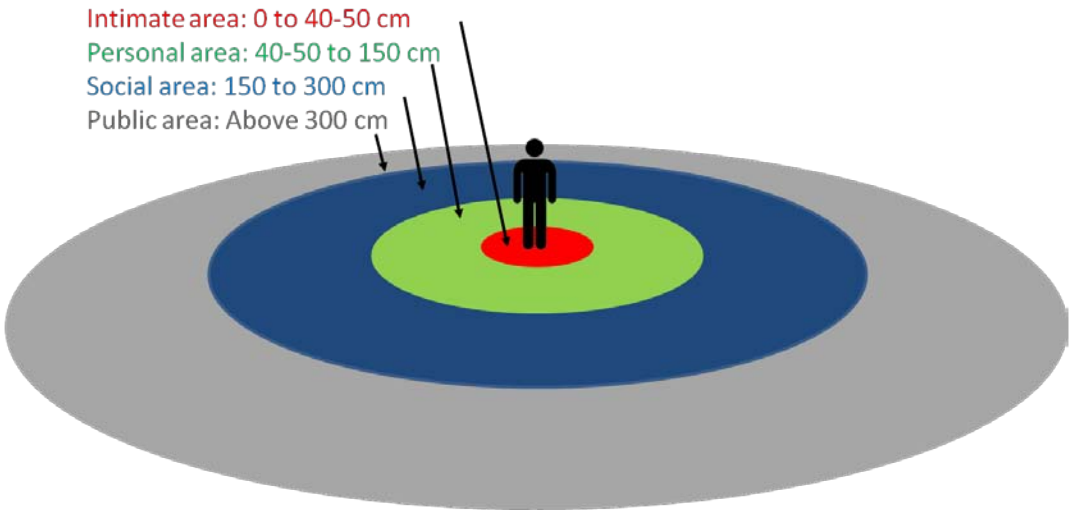


Figure 2.1. ***Intimate, personal, social and public areas of an individual; based on Proxemics theory (Hall, 1966)***

Cristani, Paggetti, Vinciarelli, Bazzani, Menegaz and Murino (2011) substantiated the proxemics theory by studying 13 individuals involved in casual standing conversations where the social relations of the participants were known prior to the experiment. They video recorded unconstrained interactions of the participants and used computer vision techniques to measure the interpersonal distances from the recordings. The result of this study showed that subjects with more intimate social relations tend to get closer in a casual conversation setting. Moreover, Cristani et al.'s study confirmed the four areas defined in proxemics theory of Hall (1966) and reported that if the space available to the subjects is reduced, the size of the four areas will reduce as well.

The empirical studies that substantiate proxemics theory are not limited to real-life human-to-human interactions; even in virtual immersive environments, humans show distance regulating behaviors when approached. An example is an empirical study by Friedman, Steed and Slater (2007) which takes place in Second Life (Linden Lab, 2003). In Second Life players have graphical embodied representations of themselves called avatars that they use for interacting with one another. In addition to the avatars, there are also computer controlled autonomous virtual humans in Second Life. Friedman et al. found that when approached by a virtual human, humans show distance regulating behaviors through their avatars. The same phenomenon has been reported by Bailenson et al. (2003). In addition to confirming the distance regulating behavior, Bailenson et al. found that the direction of approach and mutual gaze can also affect the interpersonal distance. Lastly, in an empirical study on human's arousal in immersive virtual environments (Llobera, Spanlang, Ruffini & Slater, 2010), a similar reaction is reported. Llobera et al. state that there is a direct relationship between the interpersonal distance and the electro-dermal activity of the human whose avatar is being approached by a virtual human.

Although theories on dyadic spatial behavior are essential for understanding social spatial behavior of humans, they are not sufficient for describing larger scale spatial interactions of an individual with groups. The next section is dedicated to theories about human's spatial behavior in group dynamics.

2.2.2. Spatial Interactions with Groups

In an empirical study aimed at classification of non-verbal behaviors Jayagopi, Raducanu and Gatica-Perez (2009), state that the objective of a group directly influences the group dynamics. For example, competitive groups like in a debate, require a different arrangement than collaborative groups. The set of non-verbal behaviors used by each group type can also be differentiated. Conversational groups are no exception either; there are theories that describe the spatial arrangement of group members in a conversational group. One such theory is the F-formation theory (Kendon, 1990).

Kendon (1990) defines a *transactional space* in front of every individual that they direct their attention into. He claims in a conversational group, members arrange themselves so that their transactional spaces overlap and a joint transactional space is created which provides direct, equal and exclusive access to the conversation to all members. This arrangement is called an F-formation and the joint transactional space is referred to as o-space (Kendon, 1990). In addition to o-space, there are p-space and r-space in an F-formation; p-space is a ring-shaped area around the o-space in which members of the conversation stand, and r-space refers to any place in the environment outside p-space and o-space. When there are more than two members in the conversational group, providing direct and equal access to all members is achieved by a circular arrangement, which is displayed in Figure 2.2.

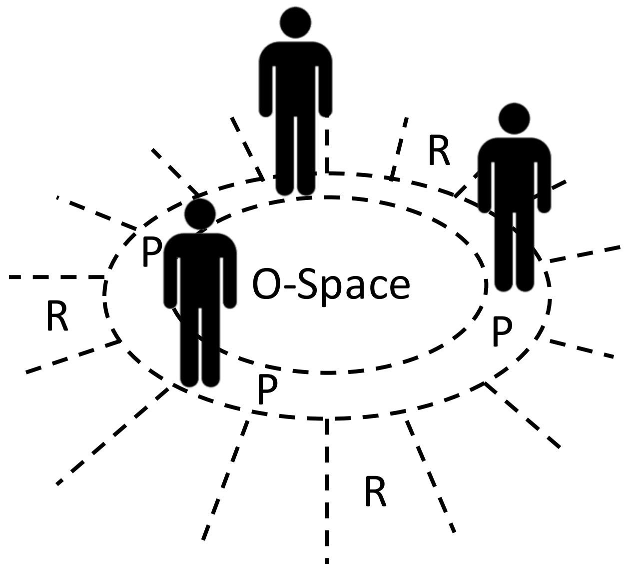


Figure 2.2. A three person F-formation with circular o-space. Adapted from Kendon (1990)

Moving forward to spatial interactions of an individual with several groups in a social environment, one can find a big gap in social psychological studies. We can find virtually no psychological theory that explains human's spatial behavior in interaction with several groups over a long period of time. Also there is a remarkable lack of studies that track human's spatial behavior in larger scale group interactions.

The empirical study of Dong, Lepri and Pentland (2011) is one of the few studies concerned with social spatial behavior of humans over a long period of time. They tracked a group of MIT dorm residents using their mobile phone data over nine months and reported that humans' social relationships and their spatial-temporal behaviors co-evolve. In other words, friendship with a group of people means an individual spends more time with that group in a common place and vice versa. Although providing such evidences for existence of a relationship between a social psychological phenomenon and human spatial behavior is helpful, we require a more specific explanation of how these relationships work. To be precise, knowing that a relationship exists does not replace a psychometric function that describes the relationship. Such a psychometric function for explaining larger scale human social spatial behavior is absent in psychological literature; but there are theories and constructs on behavior regulating mechanisms that can help in clarifying human's spatial action selection in temporally large scale social scenarios. Boredom and habituation effect are examples of these behavior regulators that we describe in the next section.

2.2.3. Mechanisms of Social Behavior Regulation

Groves and Thompson (1970) defined a dual process of habituation and sensitization that can be used as a method of behavior regulation. Habituation effect in their definition is when a subject's response to a stimulus decreases as a result of being repeatedly exposed to it. Sensitization is the opposite effect that describes an increase in subject's response to a habituated stimulus, following extra or alternative stimulus. In their experiments, Groves and Thompson gave trains of single-shock pulses to the skin of an anesthetized cat using different frequencies and studied the hindlimb flexation reflex of the cat as the response. Figure 2.3 shows the occurrence of habituation in two frequencies of giving the stimulus.

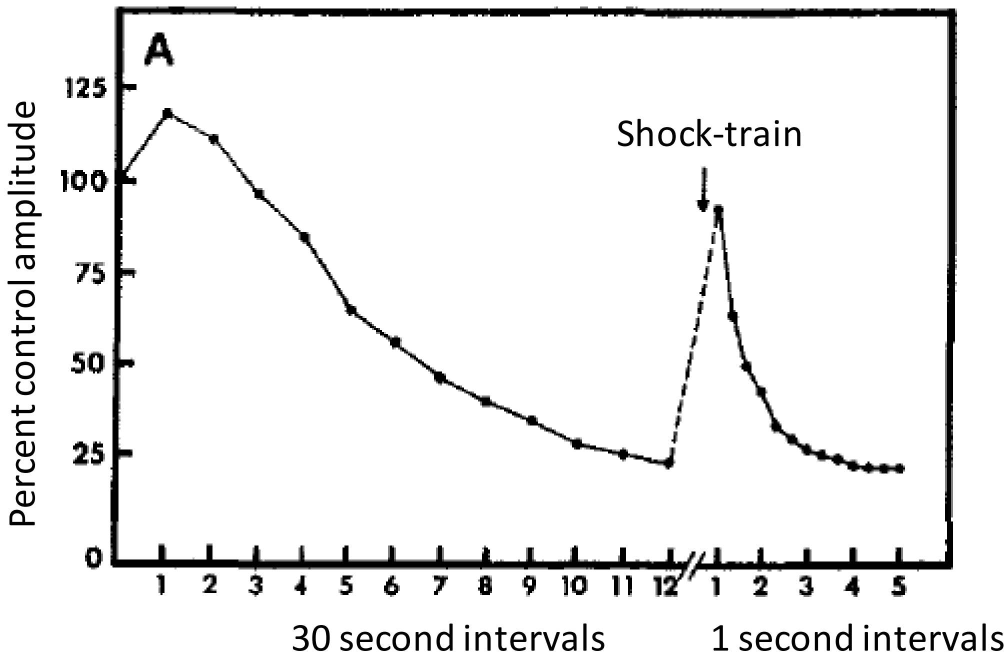


Figure 2.3. Habituation effect in Groves and Thompson's experiment on a cat's response to skin shocks. Adapted from Groves and Thompson (1970) with permission.

In addition to habituation, there is also the boredom mechanism for behavior regulation. Boredom mediates between the psychological processes influencing social spatial behavior, and provides a novelty homeostasis. Hill and Perkins in (Hill & Perkins, 1985) claim that when an individual subjectively perceives a task as undifferentiated and monotonous, boredom occurs. Personality factors and environmental stimuli can influence when exactly an individual gets into the boredom state; but boredom eventually occurs as the individual is repeatedly exposed to the same task over a period of time. According to Hill and Perkins, to get out of boredom state, the individual searches for additional or alternative stimuli in the task or from the environment. If no such stimuli can be found, the individual experiencing boredom will abandon the task and leave the field if free to do so. Geiwitz also confirms the effect of monotony on boredom and claims that boredom can be produced by increasing monotony (Geiwitz, 1966).

Besides behavior regulating mechanisms of habituation and boredom, there is also an abstract process describing humans' social behavior from an interaction point of view, which can be employed as a general guideline for social behavior regulation. This process is called *engagement process* defined by Sidner, Kidd, Lee and Lesh (2004) as: "the process by which two (or more) participants establish, maintain and end their perceived connection". Engagement process is motivated by an individual's interest in interacting with one or more other individuals and this interest results in the subject making initial contact with other individual(s). From that point forward subject constantly re-evaluates the motivation and checks if the other individuals are still taking part in the interaction. Accordingly the subject decides on whether to stay involved in the interaction or end the connection. Figure 2.4 illustrates the engagement process of a conversation group from Peters, Pelachaud, Bevacqua, Mancini and Poggi (2005).

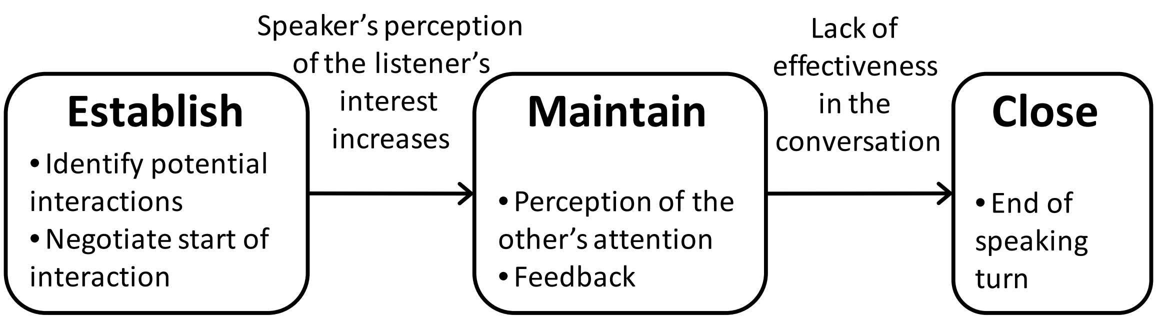


Figure 2.4. Interaction phases in engagement process of a conversational group. Adapted from Peters et al. (2005)

The psychological theories about social spatial behavior, along with behavior regulation mechanisms, form a reference for human-like social spatial behavior. In the next section we continue with a review of existing models of spatial behavior generation as baselines for generating human-like behavior.

2.3. Models of Spatial Behavior Generation

In this section we provide the reader with an overview of the existing models of spatial behavior generation for group dynamics. The challenging areas of spatial behavior generation are navigation, steering, locomotion, scenario authoring and visualization (Kapadia & Badler, 2013). Navigation and steering are concerned with planning a collision-free global path for the virtual human and moving it along the planned path while avoiding both static and dynamic obstacles. The other challenging areas, locomotion, scenario authoring and visualization are focused on realizing and animating this movement with respect to locomotion capabilities of the virtual human as well as narrative constraints of the scenario. Social spatial behavior generation imposes yet another challenge which is planning the timing and position of the virtual human according to the internal dynamic model of social motivation for movement. In the next section we provide an overview of existing approaches to address navigation and steering challenges for group dynamics.

2.3.1. Approaches to Navigation and Steering

There are two main approaches to navigation and steering for generating group dynamics: particle-based and agent-based (Pedica & Vilhjálmsson, 2008). These two approaches are differentiated by the order of magnitude of the group being simulated, as well as the level of complexity of each individual.

Particle-based Navigation and Steering

In the particle based-approach, the number of individuals, or particles, is large while all individuals are simple and similar. The main focus of this approach is on the whole system and its global collective behavior rather than the interactions between particles. Through a centralized application of physical or statistical models on all particles, a particle-based system generates or describes complex global crowd behaviors. Particle-based approach is suitable for modeling crowd behaviors, schools of fish and flocks of birds, and exhibits high performance. We can distinguish statistical and physics-based models in this approach.

On one hand, there are statistical particle-based models that describe the flow of crowds using statistical relations. For instance, Milazzo, Rouphail, Hummer and Allen (1998) employed a regression model to describe turning behaviors for a large group of vehicles in a congested turn. Lovas (1994) offered a queuing model for modeling flow of pedestrians in a network of walkway sections. Figure 2.5 shows two examples of their walkways. Lovas used a Markov chain model to describe movements of pedestrians from one node of the walkway network to another.

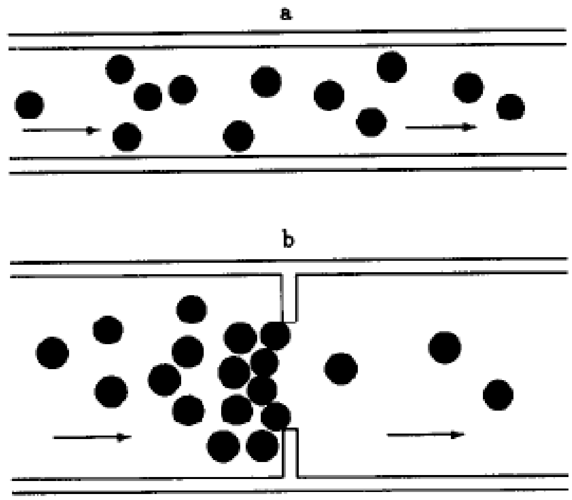


Figure 2.5. ***Unidirectional flow of pedestrians in statistical particle-based model of crowd simulation by Lovas (1994). Image from Lovas (1994): a) flow through a corridor; b) flow through a doorway of the same width***

In a similar work, Garbrecht (1973) provided a transition matrix model to predict distribution of pedestrians over a network of paths in a mall. Finally, Ashford, O'Leary and McGinity (1976) designed a stochastic queuing model to describe passenger behaviors in airport terminals.

Physics-based models on the other hand, use physical phenomena like potential fields or fluid dynamics to simulate the behavior of crowds. For example, Treuille, Cooper and Popovic (2006) simulated flow of crowds by combining a global potential field navigation method with a local collision avoidance solution. Couzin, Krause, James, Ruxton and Franks (2002) used three proximity forces influencing the velocity of particles to generate schooling behavior. Helbing modeled the crowd as a fluid (Helbing, 1992) and applied a Boltzmann-like gas kinetic model of fluid dynamics to describe the collective crowd movement through a channel. Similarly, Heïgeas, Luciani, Thollot and Castagné (2010) and Henderson (1974) used fluid dynamics to model flowing and jamming behaviors of crowds. Although particle-based models are highly efficient in macroscopic simulation of crowds, they are incapable of simulating interactions between individuals.

Agent-based Navigation and Steering

For modelling detailed group dynamics, agent-based approaches are employed. In an agent-based approach, the number of individuals is smaller compared to particle-based approaches, and each individual is equipped with simple to complex behaviors. Sophisticated collective group behaviors emerge from this type of model as a result of individual behaviors. We continue this section with an overview of the existing agent-based models, ranging from models for navigating larger scale groups, to smaller scale group navigation models emphasizing on social interactions between individuals.

Agent-based models for navigating larger scale groups of individuals are similar to particle-based models in the sense of being efficient in simulation of crowd behaviors. However, agent-based models have a distributed architecture whereas particle-based ones are more centralized. Particle-based models plans a specific type of movement for the crowd, and then realize it by applying forces on all particles, whereas in agent based models, crowd movements emerge from individual behaviors. Examples of agent-based crowd and group navigation models are presented in the rest of this section. The first few examples model larger scale group behaviors while the remainder of the section is dedicated to models of spatial interaction for smaller groups of social characters.

Reynolds (1987) simulated the aggregate motion of a flock of birds using a distributed agent-based approach. In this work, each bird is navigated according to its local perception of the environment as well as the rules of physics applicable to its motion. There are three simple behaviors all birds follow that result in flocking behavior for the whole group; these behaviors are collision avoidance, velocity matching and flock centering that keep all the birds together while maintaining minimum distance among them. In a similar distributed model, Reynolds (1999) produces path following, leader following, queuing and flocking behaviors for a crowd of simple vehicles. He achieves these behaviors by adding a steering motor force to each vehicle that enforces *seek*, *flee*, *arrive*, *avoid obstacles* and *wander* behaviors.

Moving to a more fine-grained structure with the focus on social interactions between smaller groups of individuals, there are works of Musse and Thalmann (2001) and Ulicny and Thalmann (2001). Musse and Thalmann simulate crowd behavior in real-time using a hierarchical structure to describe the crowd members. This structure consists of individual agents, groups and crowds; among which the groups are the most complex entity with various degrees of autonomy. They utilize a complex finite state machine to determine the behavioral rules, events and reactions that are followed by groups, and eventually control the crowd behavior by guiding the groups. Using a similar automata model for selecting the high-level complex behavior of the individuals, Ulicny and Thalmann also simulated crowd behavior in an urban emergency situation. These hierarchically controlled models, although more focused on the details of interaction among smaller building blocks of the crowd, do not take into consideration the rules of social interaction between individuals, like the rules governing conversations.

In a smaller scale scenario, Rehm, Andre and Nischt (2005) focus further on social rules of inter-personal interaction and build a model of social group dynamics inspired by theories from social sciences. They use proxemics theory (Hall, 1966) along with theories of conversational group formation, to simulate a scenario in which a single character joins another character for the purpose of meeting friends or building relationships. At the core of their model is how the inter-personal relationships evolve over time and the way this change influences the dynamic distance and relative orientation of pairs of agents in conversation. Relative to the context is their approach of using social theories to model distance and orientation regulating behaviors between two participants. In similar approaches, Rist and Schmitt (2008) employed simple liking relationships to emulate group dynamics in a person-to-person negotiation scenario; while Pynadath and Marsella (2005) simulated a bullying scenario in which the character's beliefs about other characters is the key factor in social interaction.

Although spatial behavior generation in a dyadic scenario is essential to modeling social navigation, it is neither complete nor sufficient in the sense that a full simulation of group dynamics requires more than a pair of members in a group. Additionally, there are other social rules governing a conversational group of more than two participants that should be considered in modelling group dynamics.

In the direction of modelling social spatial behavior of a virtual character interacting with a multiparty conversational group, we can find interesting models such as Jan and Traum (2007) and Pedica and Vilhjálmsson (2008). Jan and Traum provide a social navigation model for a virtual character that joins a conversational group using social force field navigation. Positioning the character to properly join the group is performed in this work based on proxemics theory (Hall, 1966) as well as the F-formation theory (Kendon, 1990). In other words, social rules of positioning and distance regulation are followed not only in the smaller scope of character-to-character interactions, but also in the larger scope of character-to-group interactions. This is very close to the approach of Rehm et al. (2005) but more complete in the sense of considering a multiparty conversation.

To navigate the character toward the conversational group, Jan and Traum (2007) utilize a social force field model consisting of the four forces; these forces are applied on the character to attract it toward the speaker of the group, repel it from outside noise, repel it from getting too close to the group members, and force it toward being a part of circular formation of the group. These forces are continuously evaluated to navigate the character toward a certain position in the group, relative to the position of the other group members. Although this work shows a major step forward in modelling spatial interaction of a virtual character with a conversational group, it suffers from two important issues. First, this model generates positional information for navigating the character, but the appropriate orientational information is missing from the model. Second, the forces result in reactive behavior for the virtual character; meaning that an undesired social situation should arise to activate the related force and no preventive mechanism is included.

The most promising work in this area is by Pedica and Vilhjálmsson (2008). The social navigation model introduced in this work covers generating both positional and orientational information for navigating the character. Similar to Jan and Traum (2007), Pedica and Vilhjálmsson also benefit from a social force field model for navigating a virtual character toward a conversational group. This force field is built according to three conversation-based behaviors that are intended to keep conversation’s cohesion and equality, and maintaining a minimum distance among members of the conversation. These behaviors are the main drivers of the three corresponding social forces which are cohesion, equality and repulsion forces. Group selection is based on closest distance to the virtual character in this model, and cohesion force attracts the character toward the group while the other two adjust its position in the group.

The social navigation model of Pedica and Vilhjálmsson (2008) adds orientational information to that of Jan and Traum (2007) but it is still incapable of generating preventive spatial behavior in cases of undesired social situations. Moreover, in order for the generated behaviors to be more human-like in this model, group selection process needs a more realistic motivation than the closest distance between the character and the group. As a result of the un-realistic group selection, this model falls short in simulating a temporally large scale social scenario consisting of several groups and a virtual character interacting with more than one of them. Finally, adding a dynamic internal motivation for group selection to Pedica and Vilhjálmsson's model can provide mechanisms for group-leaving and group-revisiting, which we believe are essential for a complete human-like social spatial interaction simulation with groups.

Besides the different approaches to navigation and steering for virtual humans, there are general guidelines and frameworks in the literature for designing social navigation models. In the next section we describe one of these frameworks suggested by Spence (1999).

2.3.2. General Navigation Framework

In this section we describe the general navigation framework (Spence, 1999) cited by Riedl (2001). The purpose of this computational framework is to reduce decision making and action selection in social navigation models to the minimization of cognitive costs. Riedl describes Spence's general navigation framework as an iterative cognitive process consisting of four stages: browsing, modeling, interpreting and refining browsing strategy. In the browsing stage, the navigator perceives the information that can be elicited from the environment. In the modeling stage, the navigator builds an internal model of the perceived information to understand the global picture of the environment as well as what content is perceptually available. In interpretation stage the navigator uses its internal model to decide if the goal has been reached yet, and finally if the goal has not been reached, the navigator refines its browsing strategy and chooses a new direction for movement. Spence's general framework of navigation only suggests the general outcomes of the four stages of navigation and does not provide details about how these stages are performed.

2.4. Summary

In summary, we provided reviews on two important domains in this chapter that are the base to our social navigation model. These domains are psychological information on social spatial behavior, and existing models of generating such behavior for virtual characters. The first domain acts as the reference implementation while the second provides a baseline for building our model. We reviewed psychological studies and theories that described social spatial behavior of human in dyadic interactions as well as larger groups. We talked about the gap in psychological literature for studying social spatial behavior over a long period of time and how behavior regulating mechanisms can be employed to fill this gap for generating human-like behavior.

Moreover, we reviewed two approaches to steering and navigation in existing models of generating social spatial behavior: particle-based and agent-based approaches. We study these models in order to find a state-of-the-art social spatial behavior generation system that can be employed as the baseline for our solution. Lastly, we described a general framework for designing social navigation models. In the next chapter, we describe how we employed the psychological information as well as steering and navigation solutions to build our own social navigation model.

3. Model

3.1. Overview

In this chapter we propose a social navigation solution capable of generating human-like spatial behavior for virtual game characters. Our solution is based on state of the art models for navigation and steering while our focus is employing a more realistic and dynamic motivation for action selection. Such motivation can result in the generation of human-like spatial behavior over a longer period of time compared to the currently available social navigation models. Also, we delegate the infrastructural tasks of obstacle avoidance, movement realization and animation to an existing behavior realization framework.

We build our social navigation solution for a social scenario that contains several groups of virtual characters and interacting with these groups translates to joining, leaving and revisiting them for a virtual character. Thus, our social navigation solution provides mechanisms for generating group-joining, group-leaving and group-revisiting behaviors. The core driver for these three behaviors is the virtual character's interest in engaging interactions with group members. Interest, as a wide psychological area, can have many manifestations within the simulation of a virtual character's social spatial behaviors. For our work, we specifically use interest to guide our social navigation solution. Selection of groups to join in our model is based on the interestingness of groups for the virtual character; while the dynamic changes in the interestingness value of groups trigger the group-leaving behavior in the character. Finally, a restoration of the same interestingness value makes group-revisiting behavior possible.

Description of the scenario-specific details of our work comes next, followed by the abstract view of our proposed solution. We develop our social navigation model step by step based on the model proposed by Pedica and Vilhjálmsson (2008). We describe shortcomings of our base model and the improvements we made to fix them. Finally, we employ the psychological notion of boredom and habituation as behavior regulators in our model. These regulators influence the social motivational value of groups for the virtual character, and lead to group-leaving and group-revisiting mechanisms in our social navigation model.

3.2. Problem Specifications: The Scenario

As noted earlier in this chapter, we are interested in providing a social navigation model for virtual game characters that includes group-leaving and group revisiting mechanisms as well as navigating the character toward groups. To build this model we first need to specify our scenario consisting of the social setting and its actors.

The scenario that we consider throughout this chapter is an abstract social situation that can represent a wide variety of real-life social scenarios like cocktail parties, job fairs or casinos. In this scenario, we have a virtual room of size $m \times n$ units, with one or more groups of virtual characters located in it. In addition to the groups, we have an individual virtual character called *subject character* that exhibits the social spatial behaviors our model generates. The subject character moves between different groups and engages in interactions with them at different points in time for the virtual purpose of exchanging information. The groups on the other hand, are conversational groups formed by three or more other virtual characters that are of social motivational value to the subject. It is worth mentioning that we are only interested in generating social spatial behaviors that are detectable from a long-shot distance. There are numerous studies on the social behavior of virtual characters in a close-up social situation such as gaze behavior and facial expressions, whereas from the long-shot perspective, studies are fewer and sparser.

Figure 3.1 provides a visual summary of our scenario with three groups. The rest of this section is dedicated to providing detailed information on the attributes of group members, groups and the subject character.

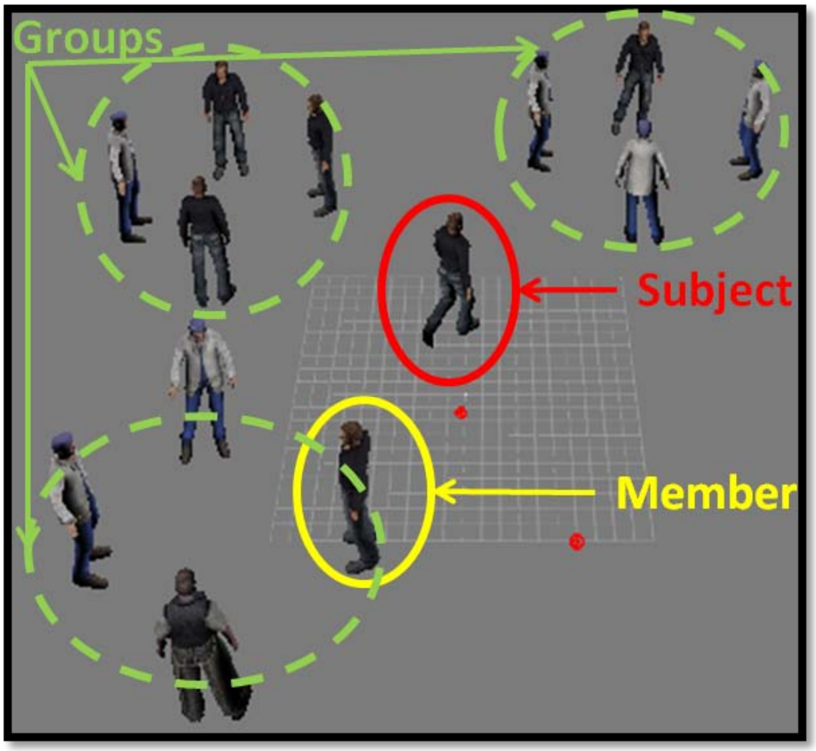


Figure 3.1. ***Visual summary of our scenario in a case with three groups; group members are forming the groups and their attributes while the subject character affects these attributes by joining and leaving the groups***

3.2.1. Group Members

Group members are virtual characters in our scenario that form the social setting by standing in our conversational groups. In addition to having access to their real-time position and rotation information, each group member has two other attributes: an interestingness value and an activity level. Interestingness of a group member is defined as a relative attribute to another virtual character, and indicates how desirable the character finds the member for engaging in interactions with. In other words, this score shows the value that the virtual character attributes to interacting with a group that this member is a part of. The source of this interestingness value can be a wide variety of a member's personal or social attributes such as the member's gender, appearance or relative status to the character. Presumably, people are more interested in interacting with or feel the need to talk to their boss compared to a stranger. The interestingness value can also come from personality factors of members; for example a high interestingness value can represent a member's sense of humor that many people find desirable in a conversation.

Activity level of group members on the other hand is a representation of how actively they are engaged in the group conversation. Examples are: the number of times the member takes on the speaker role in the group or how loud a member speaks. We use the activity level of group members in order to calculate monotony score of groups which we will later benefit from in our model as a control parameter in the leave-group mechanism. The next major element in our scenario is groups, described in the next section.

3.2.2. Groups

The groups in our scenario are formed based on common attributes of their members. These common attributes do not necessarily contain the position of the members; meaning that members of a group can change positions for an arbitrary number of times during the execution of our model and still act as a united group. The position of the group can be calculated from the latest position of its members at any point in time. To refer to the exact position of a group we calculate its center; assuming the position of each group member to be a vertex of a polygon, the centroid of this polygon is the center of our group.

Also, groups come with a set of attributes in our scenario. Attributes of groups are derived entities from their members; meaning that the interestingness of a group is assumed to be the collective interestingness of its members and same pattern holds for the activity level (monotony score) of the group. At time 0 of execution, our model calculates both the interestingness value and monotony score of all groups based on corresponding attributes of their members. From this point forward the interestingness value of a group is an attribute of the whole group as a standalone entity that can later be affected by virtual characters joining and leaving it. The next section describes attributes of the most important actor of our scenario: the subject character.

3.2.3. The Subject Character

Subject character is the individual character that exhibits the social spatial behaviors our model is capable of generating in different social settings. We apply our social and psychologically based model only on the subject character to avoid a complex scenario and be able to clearly display the behavioral capabilities of this model. However, the same dynamic model can be applied to all characters in the virtual room with no additional constraints, creating a broad variety of complex life-like social situations.

Our subject character joins and leaves different groups in the virtual environment and interacts with them. The social motivation of the subject for selecting groups to join is the value that it attributes to interacting with individuals forming that group. In other words, our subject's interest in members of a group is the main driver of the group selection process in our model. We call this social motivational value the interestingness of the individual or group and we show how the interestingness of a group dynamically changes as a result of the subject joining or leaving that group.

Additionally, we assume that our subject character has perfect knowledge about its surrounding virtual environment; meaning that starting from time 0 of executing our model, the subject has access to the following information which is continuously updated by our model:

- Subject's absolute position (three dimensional) and rotation (in degrees) in the virtual room at all times
- Group members' absolute positions (three dimensional) and rotations (in degrees) in the virtual room at all times
- Access to a real-time calculation of all groups' centers based on the real-time position of group members
- Interestingness value of each group member and group relative to subject
- Level of monotony or dynamism of each group

Lastly, we have considered two personality-based attributes for our subject character which are the radiuses of personal space and social space. These personal attributes are parameters to our model and play a key role in distance regulation for the subject character. Now that we described detailed specifications of our scenario, we continue in the next section by describing our proposed solution.

3.3. Social Spatial Behavior Regulation Model

There are two key aspects to our proposed solution: using interest as the main motivation behind human-like social spatial behavior, and generating such behavior in a temporally large scale scenario. Unlike the existing approaches to social navigation, group selection in our model is not based on closest distance; we employ interest as a more realistic motivation for action selection in our model. Interest, as a dynamically changing value that the subject attributes to its interactions with others, can play a key role in generating human-like behavior over a longer period of time compared to existing social navigation models.

Moreover, our model is capable of generating the full cycle of social spatial behavior; this cycle starts with selecting the most interesting group for the subject character to join. The cycle then continues by the subject moving toward the selected group and properly positioning himself/herself within that group. In the next step, the subject virtually interacts with the group and constantly evaluates its interestingness. This evaluation leads to the final action which is leaving the current group for another one. In this cycle, we not only include the joining group process for the subject, but also go beyond and present what happens after the subject joins a group. We provide a mechanism for leaving and revisiting groups, and this is the part of scenario that we believe closes the social spatial behavior cycle. The three behaviors of group-joining, group-leaving and group-revisiting provide the groundwork for generating human-like behavior in a temporally large scale social scenario.

Based on the above requirements we start by providing an abstract state-space view of our proposed solution, which is depicted in Figure 3.2. This state-space consists of two states for our subject character: the out_group state and the in_group or joined state. In the out_group state our subject character is out of the o-space of all groups and the model is in continuous search for subject's next target group to join. Selection of the target group is based on real-time evaluation of interestingness value of groups.

While continuously updating the found target group, our model simultaneously navigates the subject character toward the latest target group. As soon as the subject reaches the circumference of the o-space of its latest target group, the transition from out_group to in_group state completes and we consider the subject has entered group.

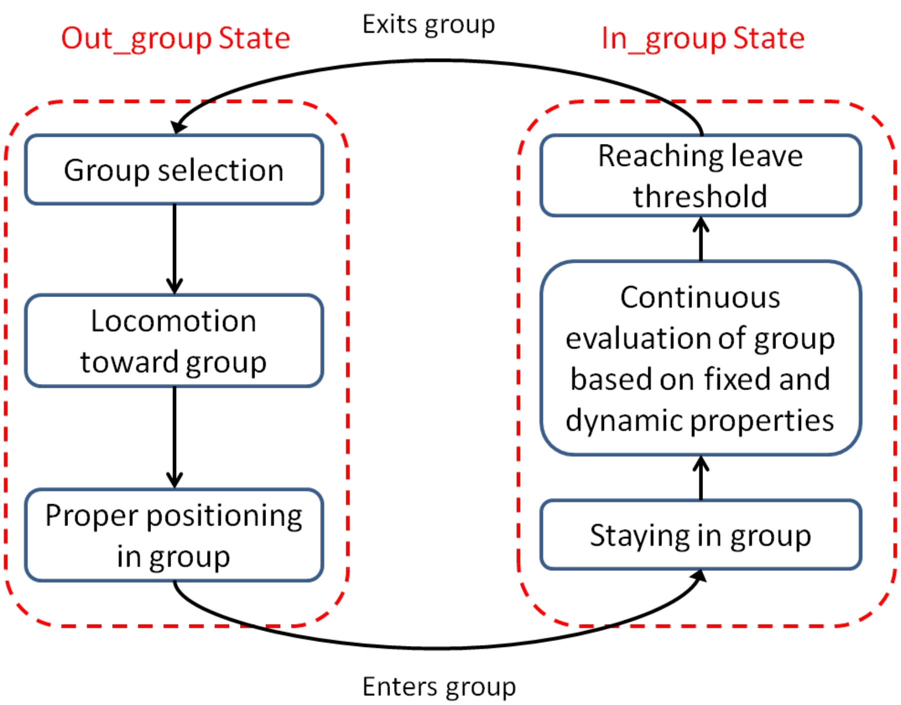


Figure 3.2. ***State-space view of our proposed solution***

While in the in_group state, because of our long-shot perspective to social spatial behavior of the subject, there is no visible spatial behavior from the subject other than staying in group. However, at the same time, our model is constantly re-evaluating the interestingness value and monotony score of the current and surrounding groups and the effect of the subject joining and/or leaving them. This real-time evaluation will eventually reach a point we call its leaving (boredom) threshold, which causes the subject character to leave the group. By leaving the group, the subject character makes the transition from in_group back to out_group state and this cycle continues as the subject character moves between different groups interacting with them.

This abstract view of our solution is supported by social navigation and interaction literature. For the rest of this section we describe how it represents a complete engagement process (Sidner et al. 2004) and how our social navigation model sits within the general navigation framework suggested in (Spence, 1999).

As a social navigation model, our proposed solution is in compliance with the general navigation framework suggested by Spence (1999). Knowing that our subject has perfect knowledge of the virtual environment at all times, the browsing and modeling stages reduce to one step in our model. This step is accessing the updated information about the position, rotation, interestingness values and monotony scores of every virtual character and group by the subject. In the interpretation stage, two possible decisions can be made depending on the state that the subject character is in: if subject character is in out_group state, the model evaluates the interestingness value of groups and decides which one is the most interesting group to be selected as the next group for the subject to join. Conversely, if the subject character is in the in_group state, our model evaluates interestingness value and monotony score of the current group and decides whether it is time for the subject character to leave the group. According to the decision made in the interpretation stage, the refinement of strategy stage either moves the subject toward the selected group or out of its current group and consequently our model moves to its next iteration.

Also from an interaction point of view, our solution represents a complete engagement process (Sidner et al. 2004). To be precise, we model the spatial behavior of our subject character in the three phases of establishing, maintaining and closing interaction with the groups. In the establishing phase, the subject character selects a target group to join based on its interest in interacting with members of that group. After the target group is selected, our model navigates the subject character toward that group. As soon as the character is positioned on the circumference of the o-space of the target group the maintaining phase starts. In the maintaining phase, the character stays within the group and our model continuously evaluates the dynamic changes in the group's interestingness value and the level of activities going on in the group. By the time the interestingness of the group drops to a leaving threshold, the character leaves the group and that is the closing of the character's interaction with that group. At this point our subject character is back in the out_group state and another spatial engagement process begins. Figure 3.3 summarizes the spatial engagement phases and their corresponding subject behaviors and transitions in our model within the subject's state space.

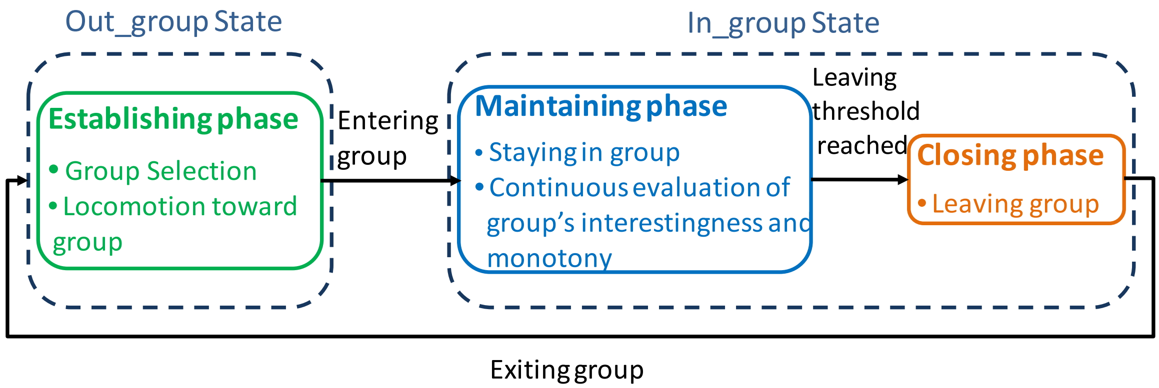


Figure 3.3. Three phases of spatial engagement in groups with corresponding states, behaviors and transitions for the subject

Among similar social navigation systems in the literature that generate spatial behavior, the best and most relevant work we found to our model is by Pedica and Vilhjálmsson (2008). Even though this work only covers the behaviors included in our out_group state of the model, we adopt it as our base model and build our interest-based in_group behaviors into it. The next section provides an overview of the work by Pedica and Vilhjálmsson (2008) as our base model.

3.3.1. Basic Social Navigation Model

Pedica and Vilhjálmsson (2008) modeled spatial behavior of a single character in group dynamics within a shared virtual environment. The groups they considered in their scenario are conversational groups and their subject's criteria for selecting a group and joining the conversation is the distance between the group and the subject. The closer the group is to subject, the higher the chance of being selected as next target group becomes. Pedica and Vilhjálmsson then defined a set of social steering behaviors to navigate their subject toward a group to join the conversation. These behaviors are *Keep_conversation_cohesion*, *Keep_personal_distance* and *Keep_conversation_equality*. The steering layer they proposed for navigating the subject character consists of a force field of three distance-based forces, each corresponding to one of the steering behaviors. These forces are: cohesion, repulsion and equality and the diagrams Pedica and Vilhjálmsson provided for each force is shown in Figure 3.4.

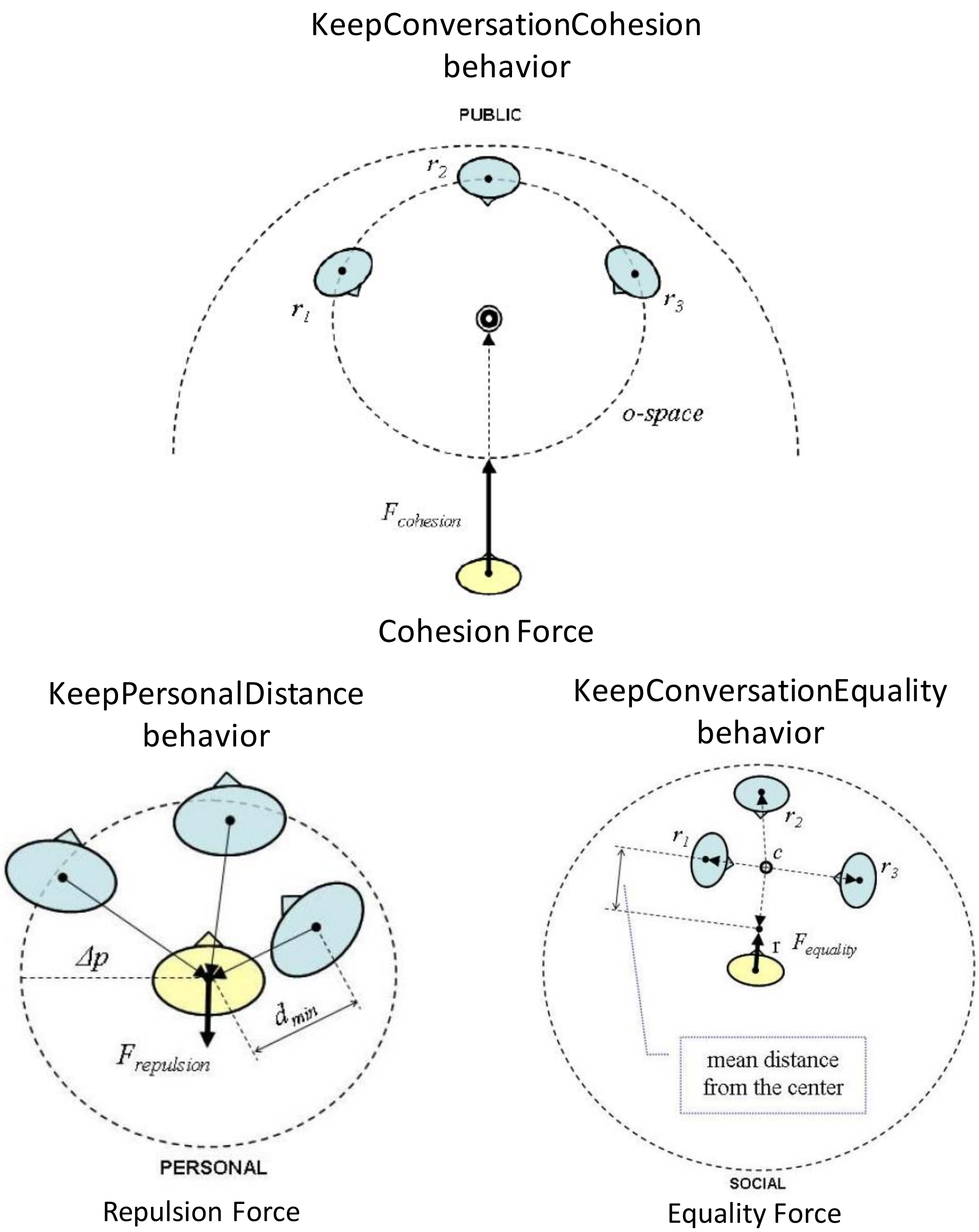


Figure 3.4. Proposed social forces by Pedica and Vilhjálmsson (2008). Adapted from Pedica and Vilhjálmsson (2008), used with kind permission from Springer Science and Business Media

Before we further describe Pedica and Vilhjálmsson's (2008) social steering behaviors, we need to briefly review the F-formation theory (Kendon, 1990). Pedica and

Vilhjálmsson used this theory to define the proper position around the center of a group at which the subject character should be placed to join the group. Kendon describes a space called *transactional space* in front of each individual that they direct their attention to. Kendon adds that in a conversation, members arrange themselves so that their transactional spaces overlap and a joint transactional space is created which provides direct, equal and exclusive access to the conversation to each member. This arrangement is called F-formation and the joint transactional space is referred to as o-space (Kendon, 1990). When there are more than two members in the conversational group, providing direct and equal access to all members is achieved by a circular arrangement, which is displayed in Figure 2.2.

Based on the F-formation theory, the proper position for the subject character to join a group is on the circumference of the circular o-space centered at the center of the group. The radius of the o-space is also calculated as the mean Cartesian distance of group members to the center of the group.

Pedica and Vilhjálmsson (2008) used this theory to define their *cohesion force* for maintaining *Keep_conversation_cohesion* behavior. Cohesion force is intended for preventing the subject from being isolated in the virtual environment and moving it toward a conversational group. On the basis of F-formation theory and in the case of groups of more than two characters, Pedica and Vilhjálmsson defined the cohesion force as in equation 1.

$$F_{cohesion} = \alpha\left(1 - \frac{s}{\|o-r\|}\right)(o-r) = \alpha(\|o-r\| - s)\frac{o-r}{\|o-r\|} \qquad (1)$$

Where $o \in R^3$ is the center of conversational group, $r \in R^3$ is the current position of the subject in the virtual environment, s is the radius of the o-space of conversational group and α is the scaling factor to adjust the magnitude of cohesion force depending on the density of virtual characters in the environment.

As soon as the subject joins a group, Keep_personal_distance behavior activates to keep a minimal distance between group members while preserving personal space of the subject. The force that maintains this behavior is called *repulsion force.* In order to define the repulsion force, Pedica and Vilhjálmsson (2008) benefited from the proxemics theory (Hall, 1966). Proxemics theory assumes four spheres around each individual interacting with another individual; these four spheres are labeled intimate, personal, social and public areas from the smallest to the largest. Based on the level of intimacy of the two individuals interacting with each other, they use one of these spheres to regulate the distance between them. Equations 2 and 3 define the repulsion force. In these equations $\mathrm{N_p}$ is the number of other group members in the subject's personal area with $r_i \in R^3$ being the current position of the ith group member in the personal area, Δ_p is the radius of subject's personal area and d_{min} is the distance to the closest group member.

$$F_{repulsion} = -\left(\Delta_p - d_{min}\right)^2 \frac{R}{\|R\|} \tag{2}$$

$$\mathrm{R} = \sum_{\mathrm{i}}^{\mathrm{N_p}} (\mathrm{r_i} - \mathrm{r}) \tag{3}$$

Comparing the repulsion force equations with the diagram of Figure 3.4 clarifies that Pedica and Vilhjálmsson (2008) assume the minimal distance of subject to group members is equal to the personal distance of the avatar.

The final behavior is *Keep_conversation_equality*, maintained by the *equality force*, which is intended for sustaining the conversation space between the virtual group members after the subject joins the group. Equations 4 and 5 define the equality force and direction respectively while Figure 3.5 depicts how this force works.

$$F_{equality} = \left(1 - \frac{m}{|\mathrm{c}-\mathrm{r}|}\right)(c - r) \tag{4}$$

$$\mathrm{D_{equality}} = \sum_{\mathrm{i}}^{\mathrm{N_s}} (\mathrm{r_i} - \mathrm{r}) \tag{5}$$

Where $\mathrm{N_s}$ is the number of group members in the subject's social area, c is the center of conversation and m is the mean distance of group members to the center of conversation.

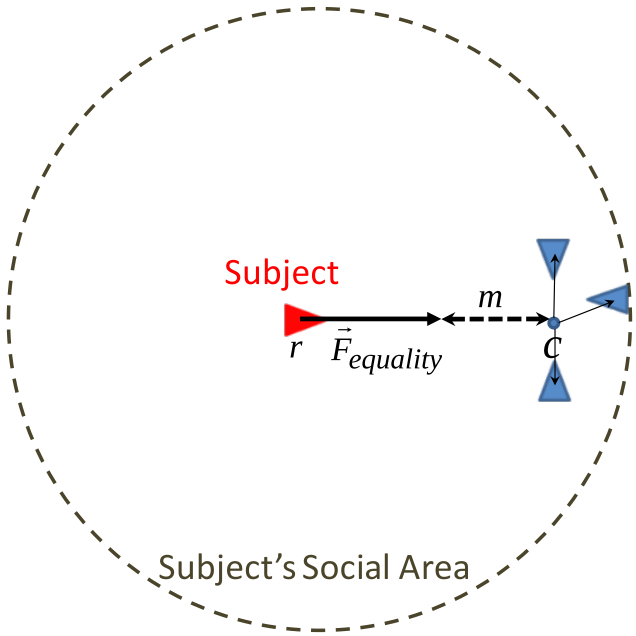


Figure 3.5. Diagram of equality force. Adapted from Pedica and Vilhjálmsson (2008)

3.3.2. Improved Social Navigation Model

Our first step in adapting the social force field model is to precisely redefine the forces using the spatial attributes of our subject and groups. This redefinition process results in a force field of two forces that we call attraction and repulsion. The redefinition process is described in the following sections.

Attraction Force

Before providing our definition of the attraction force, we need to precisely define two parameters used in this force. These parameters are center of the group and proper distance between the subject and center of the group when the subject joins the group. As seen in section 3.2.2, our virtual group members are arranged in a roughly circular formation within groups. Assuming each group member to represent a vertex in the virtual environment, we defined the center of the group to be the centroid of the polygon formed by these vertices. Equation 6 shows the calculation of the group center with N_g being the number of the group members and r_i the vector representing the position of the ith group member.

$$c = \frac{1}{N_g}\left(\sum_i^{N_g} r_i\right) \tag{6}$$

Also based on Kendon's F-formation theory (Kendon, 1990) we defined the proper position for the subject to join a group as the circumference of the o-space of that conversational group. Similar to the work of Pedica and Vilhjálmsson (2008) we considered the radius of the o-space to be the average distance of current group members to the center of the group. This proper distance is calculated using equation 7.

$$d_{avg} = \frac{1}{N_g}\left(\sum_i^{N_g} r_i - c\right) \tag{7}$$

By utilizing the above mentioned definitions for c and d_{avg} in our model, we factored the original equality and cohesion forces from Pedica and Vilhjálmsson (2008) to one force we refer to as attraction force. Attraction force is designed not only to prevent the subject character from remaining isolated in the virtual environment, but also to navigate the subject character all the way to the proper position around the center of the target group. Diagram of our attraction force is shown in Figure 3.6.

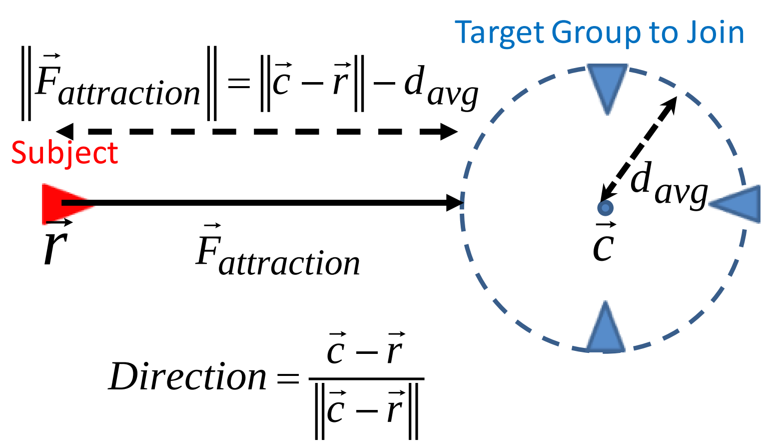


Figure 3.6. ***Diagram of the attraction force:***
Visual representation of attraction magnitude and direction

Equation 8 provides the mathematical definition of attraction force based on equations 1, 6 and 7.

$$F_{attraction} = \alpha\left(\|c - r\| - d_{avg}\right)\frac{c-r}{\|c-r\|} \tag{8}$$

Repulsion Force

The repulsion force in the original model of Pedica and Vilhjálmsson (2008) is a reactive force; it is only activated when the subject character's personal distance is already violated. That means either the subject moves too close to other group members or another moving group member steps into the personal space of the subject. In either case, only after the violation of personal distance takes place the repulsion force is activated. This activation causes the subject character to exhibit reactive behavior of backing away to regulate the distance again. We believe such reactive behavior is not human-like; instead, the repulsion force should contain a planning mechanism which activates it earlier in time before the violation of personal space happens. This gives the subject character a means to predict the violation of its personal space and avoid moving farther ahead when the group configuration results in an undesirable situation.

In order to build the planning mechanism in the repulsion force, we made use of proxemics theory (Hall, 1966). As mentioned in section 3.3.1 factor R of the original repulsion force refers to the number of group members in the subject's personal area; and if there is at least one group member in subject's personal area, it already means subject's personal space has been violated. According to proxemics theory, the next communication area larger than the personal area is the social area. If instead of checking for presence of group members in the personal area, our model checks for presence in the social area of subject, then the repulsion force can be activated earlier in time before the potential violation of personal space happens. Relying on this idea we modified the R factor in the original repulsion force to use the number of people within the subject's social area rather than its personal area. Knowing that the radius of the social area is greater than that of the personal area, this means our model will recognize group members earlier in time while the subject moves toward the group. Thus the repulsion force is activated before the personal space is violated and the resulting behavior looks more human-like. Equation 9 shows the modified R with $\mathrm{N_s}$ being the number of group members within the social area of the subject character.

$$\mathrm{R} = \sum_{\mathrm{i}}^{\mathrm{N_s}} (\mathrm{r_i} - \mathrm{r}) \tag{9}$$

Consider the subject character joining a group at time t. Figure 3.7 compares the repulsion vectors activated and calculated (a) at time t by the original repulsion force from Pedica and Vilhjálmsson (2008) and (b) at time $t - t_1$ by our improved repulsion force. Notice that in the modified version, the repulsion force activates at time $t - t_1$.

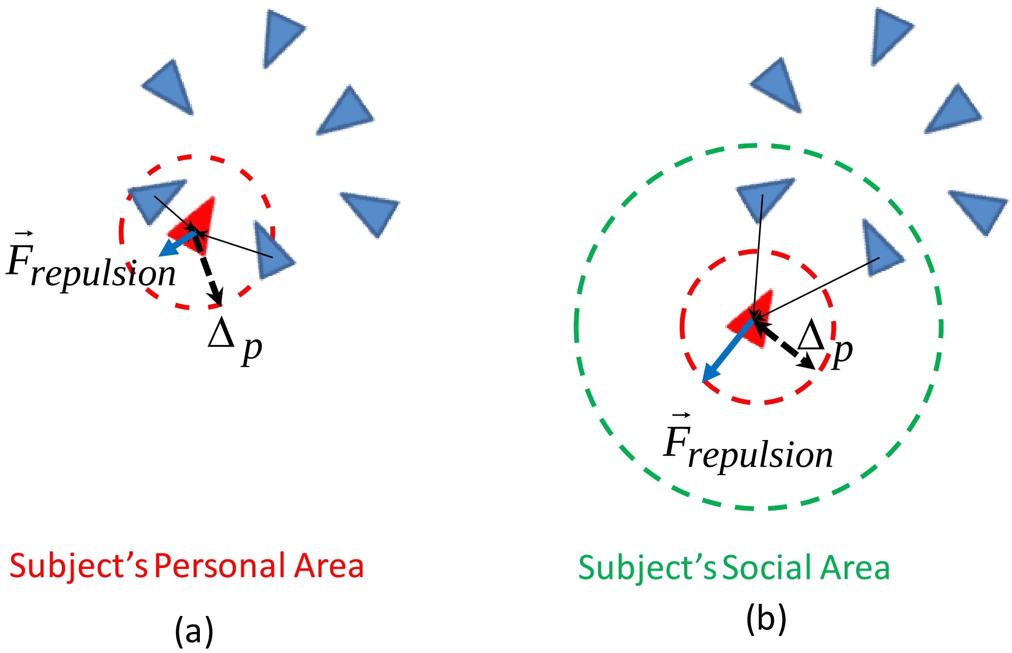


Figure 3.7. ***(a) Original reactive repulsion vector defined using character's personal area vs. (b) Improved planned repulsion vector using character's social area***

Assuming that point A in Figure 3.8 is the initial position of the subject character, our improved repulsion vector of Figure 3.7 (b) along with the attraction vector navigate the subject to point B. Notice that because of the repulsion force being activated earlier in time, the subject is neither required to step back nor its personal space is violated at any point in time.

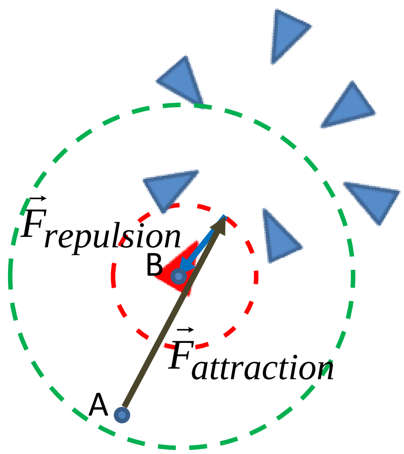


Figure 3.8. Position of the subject after joining the group using our improved repulsion force

Pedica and Vilhjálmsson (2008) presented visual results of their work in the form of videos showcasing the effectiveness of their proposed framework. However, they did not provide public access to sources of the framework for further testing of additional usecases. Our own implementation of the repulsion force on the other hand demonstrated that the magnitude of the force requires adjustment as well. The proposed magnitude of the original repulsion force sends the avatar far back from the group; thus our final improvement was to reduce the magnitude of the repulsion force. Equations 9 and 10 define our improved version of the repulsion force.

$$F_{repulsion} = -\left|\Delta_p - d_{min}\right| \frac{R}{\|R\|} \qquad (10)$$

The repulsion force of equation 10 still suffers from lack of proper direction; that means if the subject character is initially positioned inside the o-space of a group, there are cases that the repulsion force navigates the character to cut across the group rather than making it step back. Although we do not consider this a human-like behavior to cut across conversational groups, we made two assumptions about our force field model that guarantee such cases do not happen in our model at the first place:

1. At time 0, our subject character starts in the out_group state; meaning that the initial position of the subject is outside the o-space of all groups
2. The early activation of the modified repulsion force always prevents the subject character from entering o-space of groups.

Therefore our subject character never enters the o-space of any group and the static direction of the repulsion force is always the correct direction in all testcases of our model.

Although we made improvements to the original social forces by Pedica and Vilhjálmsson (2008) to build our own force field of attraction and repulsion forces, these forces are still distance-based. In the following sections we use our psychological knowledge of human social spatial behavior to further improve our model and generate social spatial behavior closer to that of humans.

3.3.3. Psychological Distance in Our Social Navigation Model

Social psychological studies suggest that a human's experience of distance is subjective. In other words, the same physical distance can be perceived differently from one individual to another. The greater the distance, the more abstract the perception of the individual becomes (Liberman, Trope & Stephan, 2007). This subjective experience of distance is called psychological distance. To account for this phenomenon, we included a non-linear mapping from physical distance to psychological distance perceived by our subject character in our model. Therefore, for every distance-based calculation in our force field model, we used the distance at which a group or a group member is perceived rather than their relative physical position.

In an effort to quantitatively model processes of social distance regulations, Gubler and Bischof (1990) proposed the Zurich model of social motivation. In this model they used a two-parameter hyperbolic function to map the physical distance to psychological distance. The two parameters to this mapping are maximum distance perceivable by the subject and mapping control parameter. Inspired by the Zurich model of social motivation, we defined our mapping from physical distance to psychological distance as shown in equation 11.

$$\mathrm{D_{perceived}}\left(\mathrm{D_{physical}},\ \mathrm{D_{max}}, \mathrm{r}\right) = \begin{cases} \dfrac{\mathrm{D_{max}} . \mathrm{D_{physical}}}{\mathrm{r} . \left(\mathrm{D_{max}} - \mathrm{D_{physical}}\right) + \mathrm{D_{max}} . \mathrm{D_{physical}}} & \text{for } \mathrm{D_{physical}} < \mathrm{D_{max}} \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

In this mapping, parameter D_{max} shows the maximum physical distance perceivable by our subject character, $D_{physical}$ is the physical distance between the subject character and the group or a group member, and r is our control parameter determining the rate at which psychological distance grows with physical distance. Both D_{max} and r are parameters of our model which not only normalize all distances to a value within $[0,1]$ interval, but also make the virtual environment scalable as well. No matter what the dimensions of the virtual room are, we can always tune the psychological distance parameters in a way that the whole room is perceivable by the character. Figure 3.9 shows a sample plot of our psychological mapping function with $D_{max} = 200$ and $r = 20$.

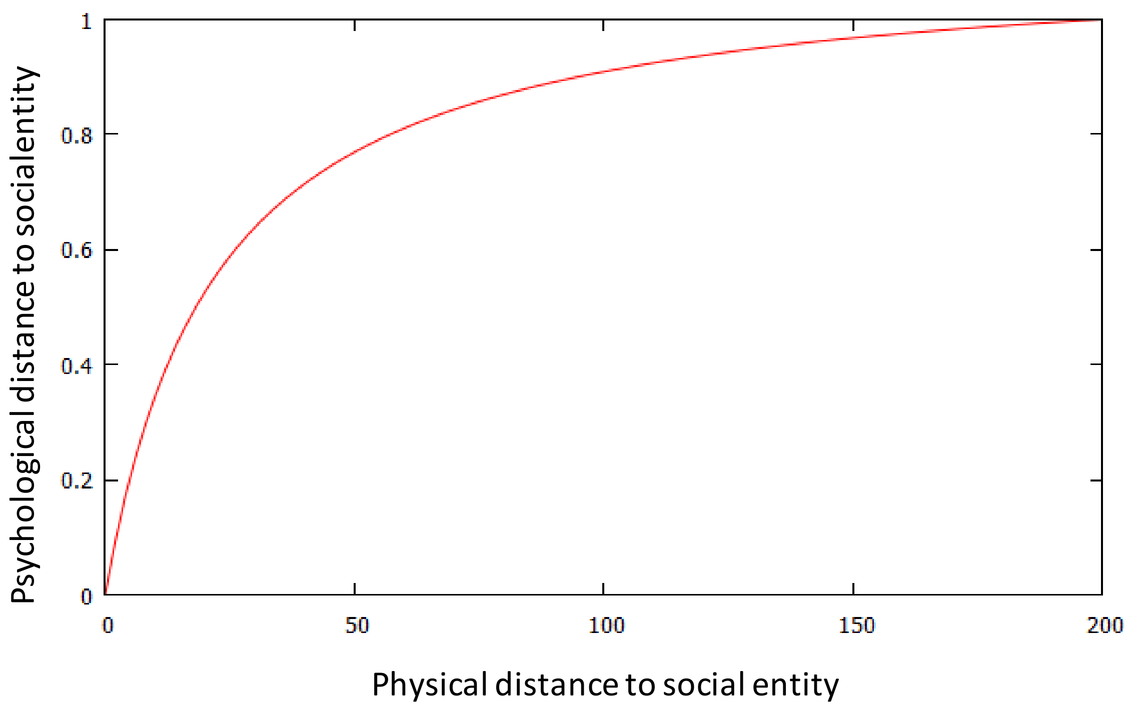


Figure 3.9. ***Our physical distance to psychological distance mapping function with D_{max} = 200 and r = 20***

Improvements we made to the social forces of Pedica and Vilhjálmsson (2008), along with introduction of psychological distance to our model, are both efforts to make the model capable of generating social spatial behavior closer to that of humans. However, the decisions our model makes based solely on these improvements are still distance-based. Looking back at Figure 3.2, our model only covers the behaviors in the out_group state so far. To go beyond the distance-based model and close the cycle shown in Figure 3.2, we introduce interest-based social spatial navigation.

3.4. Interest-based Social Spatial Navigation

As mentioned earlier in this chapter, humans subjectively attribute value to their interactions with other individuals and this value, that we call *interest*, is their motivation for engaging in interactions with other individuals. Moreover, interest as a dynamic function of time can act as the leave-group mechanism in our model. On the basis of this idea we introduce interestingness score of groups that we will use to turn our distance-based social force field into an interest-based force field. The details of how we model interest and calculate the interestingness score is described in the next section. For the rest of this section, we use $\mathrm{Interestingness}_{\mathrm{g}}(\mathrm{t}, \Delta_{\mathrm{g}})$ to refer to our interestingness score of group g as a function of time (t) and level of activities (monotony score) of the group (Δ_{g}).

The above definition for interest turns the interestingness score of groups to the main factor of group selection in our model. At any point of time when the subject character is in the out_group state, our model continuously evaluates the interestingness scores of all groups and selects the group with the highest perceivable interestingness score as the target group. Here, by perceivable interestingness score, we mean the interestingness score of the group scaled to the psychological distance at which the subject perceives that group. The attraction force that derives this process is shown in equation 12.

$$F_{attraction} = \alpha\left(Interestingness_g(t, \Delta_g)\right).\left(\mathrm{D_{perceived}}(\|c-r\| - d_{avg}, D_{max}, r)\right)\frac{c-r}{\|c-r\|} \qquad (12)$$

It is worth emphasizing that our force field model calculations are continuous in terms of time. This means that as soon as the subject character in the out_group state selects an initial target group, not only does it start locomoting toward that group; it also continues evaluating all groups' interestingness scores in real-time while moving. In case a group with a higher perceivable interestingness score is found, the subject character strays from its current path and locomotes toward the new target group. When the subject character reaches the distance d_{avg} from the center of the most recently selected target group, it has officially joined that group and the transition from the establishing phase of interaction to the maintaining phase is complete.

In the maintaining phase, our model continuously re-evaluates the interestingness score of subject's current group over time and monitors if this score drops to the leaving threshold. The only spatial behavior observable in this phase is the subject character staying at the same position within the group for an arbitrary interval in time. When the leaving threshold is reached, our subject character leaves the current group and the current engagement process moves into its closing phase. The next section provides detailed information on our interest model.

3.4.1. Interest Model and Calculation of Interestingness Score

In the previous section we discussed the establishing phase of spatial engagement in our model. We described the role of interest as the motivation of our subject character to engage in interactions with groups. In this section we focus on developing our model for interest which is the driver of maintaining and closing phases of our social navigation solution.

In order to develop our interest model, we reviewed the psychological literature on social spatial behavior. We looked for a psychometric function that models human social spatial behavior in a social setting like a job fair. What we recognized was a big gap in social psychology literature for tracking and modeling social behavior of humans in social settings over a long period of time. As seen in section 2.2, the available psychological models of human social spatial behavior are either concerned with the existence of a relationship between a social phenomenon and specific spatial behaviors of humans, or model the social spatial behaviors of an individual in a strictly limited space around the individual. As an example, a study by Dong et al. (2011) states that humans' social relationships and their spatial-temporal behaviors co-evolve; but how this co-evolution exactly occurs remains unknown.

Despite the gap for modelling large scale social spatial behavior, there are structures defined in psychology that can be employed as behavior regulators to generate human-like social spatial behavior in an engineering approach. Two examples of these structures are boredom and habituation. The works of Geiwitz (1966) and Hill and Perkins (1985) in modeling boredom as well as Groves and Thompson's theory of habituation (Groves & Thompson, 1970) came as guidelines for us to build an internal representation of interest for our social navigation solution. Inspired by the behavior regulating effect of boredom and habituation, we took an engineering approach to model interest. Assuming the individual is our subject and the task is engaging in interaction with a conversational group, our interest model works as follows: at the beginning, the collective interestingness of members of a group acts as the motivation for the subject to join the group. When the subject joins the group, its interest in interacting with the members start to decrease as a function of time which is in compliance with the habituation theory. Also, according to Hill and Perkins, boredom will eventually occur if the task remains unchanged. This is where the activity level of the group comes into play. We measure monotony of a group as the collective number of times the group members undertake an activity such as speaking. The less monotony score of a group is, the more alternative stimuli our subject can find in interacting with the group, and thus it remains in the group longer. However, the subject will eventually experience boredom in its current group at some point in time that is influenced by personality factors of the subject as well as interestingness and monotony scores of other groups in the environment. According to Hill and Perkins, this is the leaving threshold. The subject character leaves the group in order to find alternative stimuli in interacting with other groups in the virtual environment.

Hence, we initially modeled interest in our solution using a decreasing function of time which is shown in equation 13. At time 0 of joining a group, the interestingness score of that group is at its maximum value. This value is an aggregation of interestingness scores of members of that group in the initial setting. As time passes while the subject maintains its interactions with the group, interestingness score of the group decreases proportional to its monotony score. Higher monotony scores translate to faster decay and similar direct relationship holds for lower monotony scores. This monotony score is then used as a control parameter in our model of interest. In equation 13, t is the time elapsed after the subject character has joined group g, T_{max_g} is the maximum time it takes the character to completely become bored of group g and m_g is the monotony score of group g. Figure 3.10 shows a sample interestingness plot with $T_{max_g} = 10$ seconds and $m_g = 25$.

$$I_g\left(T_{max_g}, t, m_g\right) = \begin{cases} \frac{m_g.\left(T_{max_g} - t\right)}{m_g.\left(T_{max_g} - t\right) + T_{max_g}.t} & \text{for } t < T_{max_g} \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

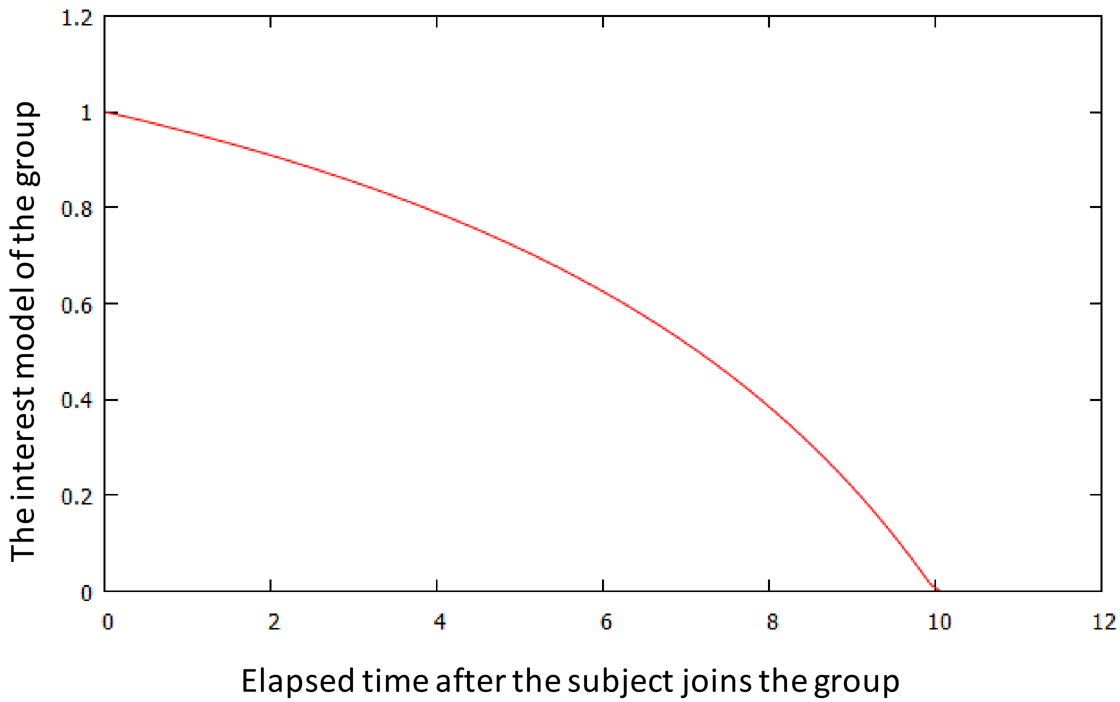


Figure 3.10. An example of interest model for group g with T-max = 10 seconds and m = 25

As mentioned earlier in this section, situational and personality characteristics of the subject have a role in determining when the boredom occurs. We reflect this in our model by incorporating a parameter called boredom threshold; that is the minimum interestingness score our subject experience a group at, before it leaves that group. We denote boredom threshold for group g by I_{min_g} in our model. I_{min_g} comprises a constant factor for personality characteristics of our subject, as well as a dynamic environmental factor that is a function of interestingness scores of other groups. The more subject character perceives other groups as interesting, the likelier that it leaves its current group. Figure 3.11 shows the leaving threshold added to the interest model of Figure 3.10. In this figure, t_{0_g} is the time at which interestingness score of group g drops to I_{min_g}.

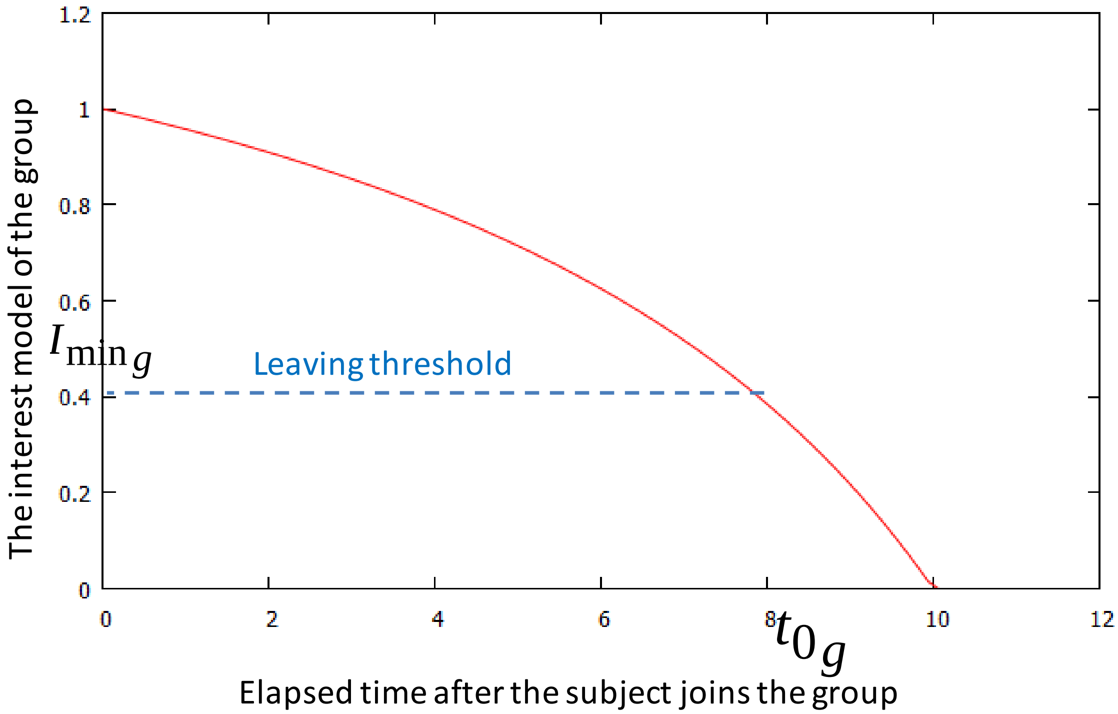


Figure 3.11. Leaving threshold in interest model of group g with T-max = 10 seconds and m = 25

When the interestingness score of a group hits the leaving threshold, transition from the maintaining phase to the closing phase of interaction happens. In the closing phase, the subject character moves away from the current group toward another interesting one. Right after leaving a group, the interestingness score of that group is relatively low compared to the others. However, the distance at which subject character perceives that group is very short as well. This in some cases, depending on the spatial distribution of groups and their interestingness scores, results in the subject returning to the same group while selecting the next target group. To prevent returning to the same group right after leaving it, we modified our interest model and included a mechanism for inhibition of return (Klein, 2000). In our mechanism resulting in inhibition of return, leaving a group causes the interestingness score of that group to immediately drop to 0. We included this shunting effect in equation 13 by modifying the time condition from $\mathrm{t} < \mathrm{T}_{\mathrm{max}_\mathrm{g}}$ to $\mathrm{t} < \mathrm{t}_{0_\mathrm{g}} < \mathrm{T}_{\mathrm{max}_\mathrm{g}}$, assuming $\mathrm{t}_{0_\mathrm{g}} < T_{\mathrm{max}_\mathrm{g}}$ is the time of reaching the leaving threshold. Figure 3.12 shows the improved version of the interestingness function of Figure 3.11 with the shunting effect resulting in inhibition of return.

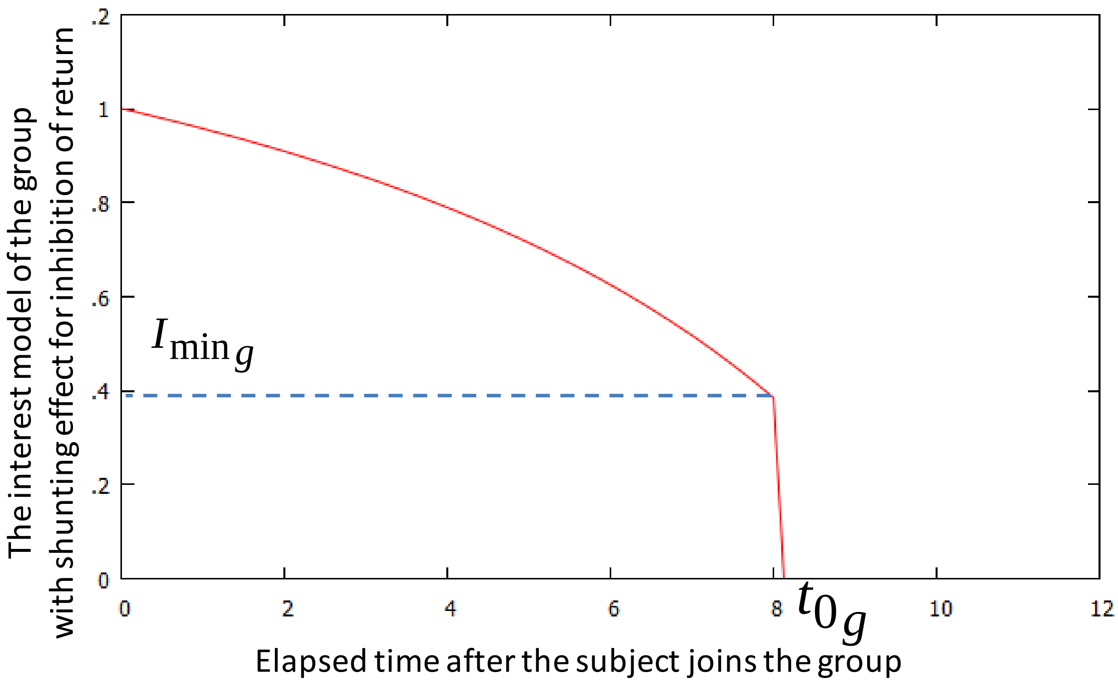


Figure 3.12. Shunting effect added to interest model from Figure 3.11 that results in inhibition of return

Finally, we claim that humans are likely to interact with a conversational group more than once in a social setting. Because of this possibility, we include a recovery part to our model of interest so that a group once left by subject can recover its interestingness over time and has the chance to be revisited by the subject later. Similar to our model of decay in interest, the recovery part is a non-linear function of time with a control parameter which again is proportional to the monotony score of the group. The recovery part of our interest model starts as soon as subject character steps out of the group and leaves it. Equation 14 defines our ultimate model of interest for group g.

$$I(t, T_{max_B}, m_B, t, T_{max_R}, m_R) = \begin{cases} \frac{m_B \cdot (T_{max_B} - t)}{m_B \cdot (T_{max_B} - t) + T_{max_B} \cdot t} & \text{for } t < t_0 < T_{max_B} \\ \frac{T_{max_R} \cdot t}{m_R \cdot (T_{max_R} - t) + T_{max_R} \cdot t} & \text{for } t_0 < t < T_{max_R} \end{cases} \quad (14)$$

Where T_{max_B} and T_{max_R} are the maximum times it takes the character to completely lose or gain back interest in current group respectively, m_B is the monotony-based control parameter for decay and m_R is the monotony-based control parameter for recovery of interest. A sample plot of our interest model based on equation 14 is shown in Figure 3.13 with $T_{max_B} = 10$ seconds, $m_B = 25$, $T_{max_R} = 30$ seconds and $m_R = 90$.

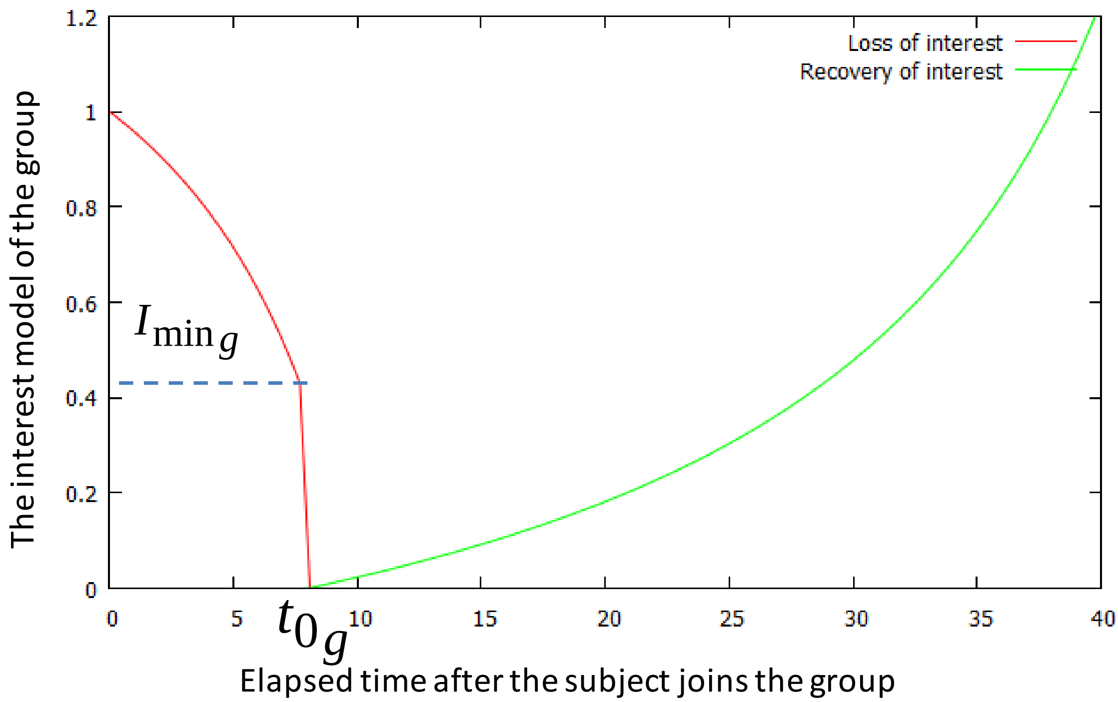


Figure 3.13. Final interest model with inhibition of return and recovery with T-max-B = 10 seconds, m-B = 25, T-max-R = 30 seconds and m-R = 90

3.5. Summary

In summary, we introduced our interest based social navigation model in this chapter. We described our general social scenario and the specific attributes of our actors in this scenario which are subject, group members and groups. Next we proposed our two-state solution which not only is in charge of navigating the subject to join a group, but also manages what happens afterwards until the subject leaves that group to join another one. We realized our two-state solution in a social navigation model based on the work of Pedica and Vilhjálmsson (2008). We made improvements to the social force field Pedica and Vilhjálmsson proposed, in order to modify their reactive forces to our planned forces. Moreover, we included the effect of human's perception in our model by utilizing psychological distance instead of physical distance. We even went beyond the distance based navigation and introduced our interest-based social navigation model which considers interest as the main motivation of individuals for interacting with each other.

We benefitted from Hill and Perkins's model for boredom (Hill & Perkins, 1985) in defining our own interest model. In our model, boredom is a behavior regulator that we use to build a mechanism for leaving groups. In an engineering approach and using the model of boredom, we defined our interest function as a decreasing function of time which is controlled by the monotony score of the group. We also took situational, environmental and personality characteristics of the subject into account for specifying an above zero leaving threshold in our interest model. We prevented consecutive cycles of join and leave of the same group using our mechanism for inhibition of return, which dropped the interestingness score of the groups to 0 at the time leaving threshold is hit. Finally, to make it possible for our subject to visit a group more than once (but not consecutively) during the simulation of our model, we added the recovery part to our interest model. Figure 3.14 summarizes our ultimate interest model.

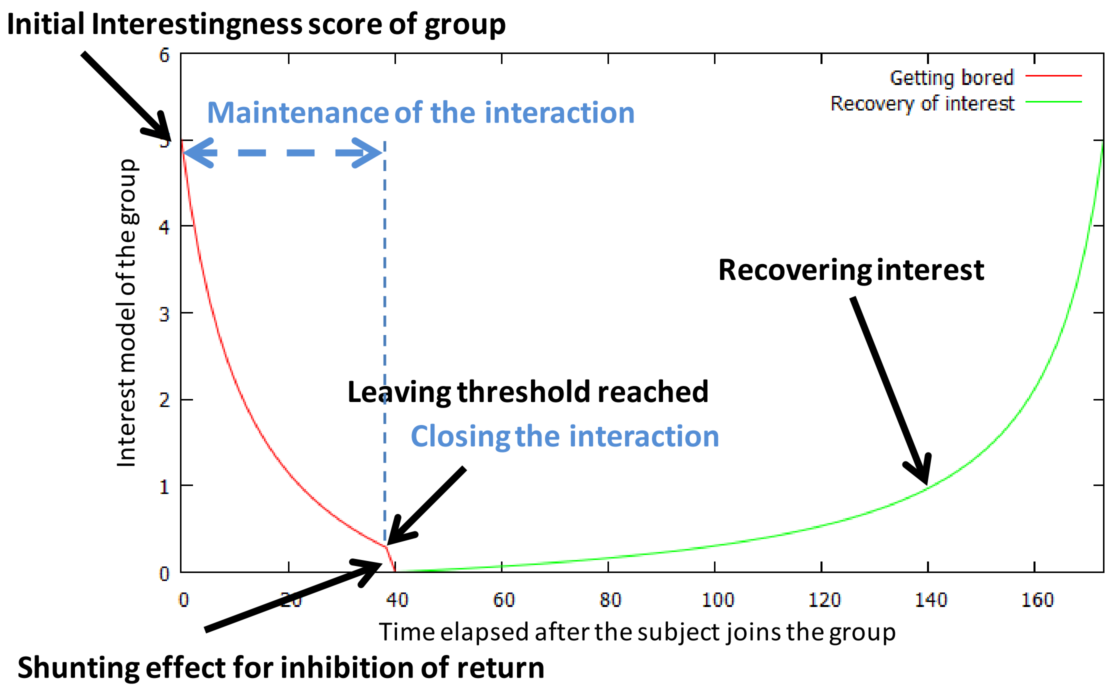


Figure 3.14. Summary of our ultimate interest model for a group

To be able to visually evaluate our model and compare the spatial behaviors it generates to those in psychological literature on social spatial behavior, we implemented it and ran several simulations. In the next chapter we describe our implementation of the model as well as the simulation results.

4. Implementation

4.1. Overview

Chapter 3 introduced our interest-based social navigation model. We created this model based on a set of available psychological theories and studies on social spatial behavior which we reviewed in Chapter 2. Our ultimate goal for this model is to generate social spatial behavior for a 3D virtual game character, closer to that of humans. Thus, the first step for evaluating our model is to implement it and run a set of simulations in order to actually see the behaviors it is capable of generating in diverse social settings. Visual comparison of the generated behavior with what we know about human social spatial behavior unveils how close we reached our ultimate goal.

When implementing a model involving embodied 3D virtual characters like our subject character or group members, appearance and rigs of the characters become as important as the behaviors they exhibit. In this context, appearance of the 3D character is its visual features like skin, hair and clothing, and by rigs we refer to the basic control structure for moving the character, like a skeleton. So, our implementation should cover 3D animation and rendering as well as social spatial behavior planning and realization. However, the tasks of animating and rendering virtual characters are complex enough for a field of study to be dedicated to character engines. These character engines can not only be in charge of animating and rendering the character, but also provide some level of autonomy in movement like path planning and obstacle avoidance mechanisms. In this implementation, we delegate the tasks of animation, rendering and behavior realization to the SmartBody platform (Thiebaux et al., 2008) and develop our own social spatial behavior planning module to plan the social spatial behaviors to be realized. Smartbody is a real-time 3D character framework developed in University of Southern California which we detail in section 4.3.

To communicate the planned social spatial behavior to SmartBody, we require a standard means of describing behaviors, for which we use Behavior Markup Language (BML) (Vilhjálmsson, Cantelmo, Cassell, Chafai, Kipp, Kopp, Mancini, Marsella, Marshall, Pelachaud, Ruttkay, Thórisson, Welbergen & Werf, 2007). We start the next section by describing the BML language and continue by pointing out the capabilities of SmartBody platform that brings our testcases to life. Then we describe the implementation of our model in run-time using a two-stage behavior generation process. In the first stage, our model is in charge of planning the social spatial behavior while in the second stage, SmartBody takes care of realizing the planned behavior. The flowchart of the social spatial behavior planning algorithm and a block diagram of the architecture of the system are provided to clarify our behavior generation process. Finally, we describe the initialization process of our model where the social spatial behavior planning algorithm is initialized with the information about the social setting and model parameters.

In addition to this documentation, we offer public access to our source codes, video results and other auxiliary resources we developed and used for the simulations through the iVizLab website[2] for further testing and studies.

4.2. Behavior Markup Language (BML)

The first step toward realizing behaviors for our virtual characters is to precisely describe the behaviors. To that end, we use Behavior Markup Language or shortly BML. According to Vilhjálmsson et al., BML is a unified way of describing both verbal and non-verbal behaviors of humans, and its key feature is independence from the particular animation method used to realize the behavior (Vilhjálmsson et al., 2007). Although other application specific languages are available for describing behaviors, they have large overlapping concepts. BML is the result of an effort to develop a common and standard specification that prevents replication of work in describing behaviors.

[2] http://ivizlab.sfu.ca/research/SocialCharacterThesis/

BML 1.0 Standard (Reidsma & Welbergen) defines BML as an XML based language that is capable of describing a list of behaviors in a <bml> block. This block can then be embedded in any larger XML code. The behaviors currently supported by BML include walking, talking, gesturing, nodding, grabbing objects, looking at objects, etc. A BML command describes each behavior by specifying its physical realization parameters as well as its synchronization constraints. By specifying these two attributes, the behavior designer can focus on designing the behavior rather than its realization. Figure 4.1 shows an example of a BML command.

There are complex software modules called BML realizers that implement the standard BML specification. Some examples are provided in CADIA ("The CADIA BML Realizer", n.d.), GRETA (Mancini, Niewiadomski, Bevacqua & Pelachaud, 2008), Elckerlyc (Van Welbergen, Reidsma, Ruttkay & Zwiers, 2009) and SmartBody (Thiebaux et al., 2008) among which we employ SmartBody for realization of behaviors generated by our model as well as animation and rendering characters. SmartBody supports the Vienna draft version of BML and its pluggable architecture is what makes it the best candidate for behavior realization in our implementation. The next section describes the SmartBody platform.

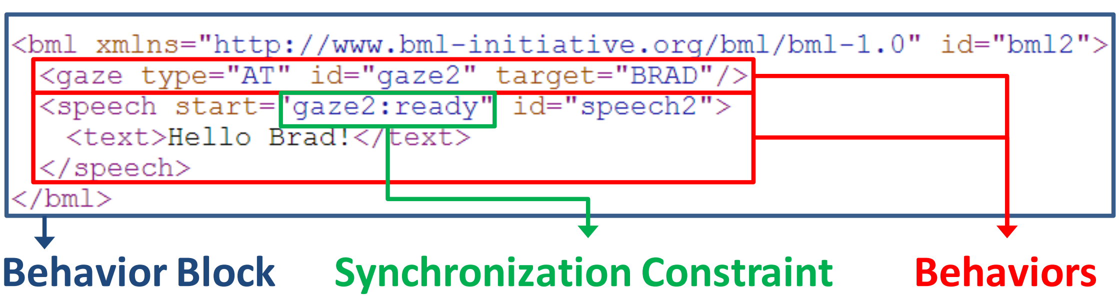


Figure 4.1. ***Example of a BML command with its physical specifications and synchronization constraints. Adapted from Reidsma and Welbergen***

4.3. SmartBody as the Animation and Behavior Realization Engine

SmartBody software (Thiebaux et al. 2008) is one of the best academic real-time character animation and behavior realization platforms available and we employ it as our backend engine in this implementation. This open-source 3D character animation and

BML realization engine is developed at the Institute for Creative Technologies, part of University of Southern California. Because of its academic base, Smartbody is commonly used in intelligent virtual agent research projects such as those of Swartout, Traum, Artstein, Noren, Debevec, Bronnenkant, Williams, Leuski, Narayanan, Piepol, Lane, Morie, Aggarwal, Liewer, Chiang, Gerten, Chu and White (2010) and Kenny, Parsons, Gratch, Leuski and Rizzo (2007). Unlike similar commercially available character platforms, Smartbody is in a close active collaboration with research scholars which results in frequent and ongoing updates and contributions to its capabilities. SmartBody provides a set of real-time capabilities for virtual characters (Shapiro, 2011) which are listed below and realized using BML:

- Locomotion: walk, jog, run, turn, strafe, jump
- Steering: avoiding obstacles and moving objects
- Object manipulation: reach, grasp, touch, pick up objects
- Lip Synchronization and speech: characters can speak with lip-syncing using text-to-speech or pre-recorded audio
- Gazing: robust gazing behavior that incorporates various parts of the body
- Nonverbal behavior: gesturing, head nodding and shaking, eye saccades
- Character physics: ragdolls, pose-based tracking, motion perturbations

SmartBody is designed as a hierarchical controller-based architecture and combines 15 controllers for hierarchically controlling body parts of the virtual character. Animation in SmartBody is a combination of skeletal animation and per-vertex morph target techniques and it has a fully featured renderer for appearance of characters including hair and clothing.

SmartBody is developed in C++ programming language, and distributed under the LGPL licence. It can be employed as a standalone system or in combination with other game engines such as Unity[3], Ogre[4], Panda3D[5], Gamebryo[6] and Unreal[7].

[3] Unity Game Engine: http://unity3d.com/
[4] OGRE – Open Source 3D Graphics Engine: http://www.ogre3d.org/
[5] Panda3D – Free 3D Game Engine: https://www.panda3d.org/
[6] Gamebryo Game Engine: http://www.gamebryo.com/
[7] Unreal Engine: http://www.unrealengine.com/

SmartBody's built-in Python interpreter enables the users to control their simulations with a Python API; this API provides access to SmartBody's internal objects for starting and stopping simulations, creating or removing virtual characters in the scene, configuring characters and the camera, etc.

The above animation and behavior realization capabilities, along with detailed documentation and its academic base, made SmartBody an excellent backend engine for us to simulate our model with. Our implementation of the social spatial navigation model involves two processes: initialization of the model and run-time planning and realization of social spatial behaviors. In the next section we describe how we implemented our model in run-time using SmartBody, and the initialization process is explained afterwards.

4.4. Implementation of Our Social Navigation Model in Run-Time

This section details implementation of our social spatial navigation model at run-time. In other words, we assume that our model is already correctly initialized with parameter values and the initial scene information, and ready to start simulation. Details of the initialization process are explained in the next section.

In our implementation, we use a two-stage spatial behavior generation process at run-time; in the first stage, our social navigation model plans the position and rotation of the subject character through a social spatial behavior planning algorithm. This plan is then communicated via a BML command to SmartBody. In the second stage, by executing the BML command, SmartBody realizes the spatial behavior which results in an update in positional and rotational information of the subject. Finally, our social spatial behavior planning algorithm obtains this updated information for its next iteration of planning. This two-stage spatial behavior generation process is illustrated in Figure 4.2.

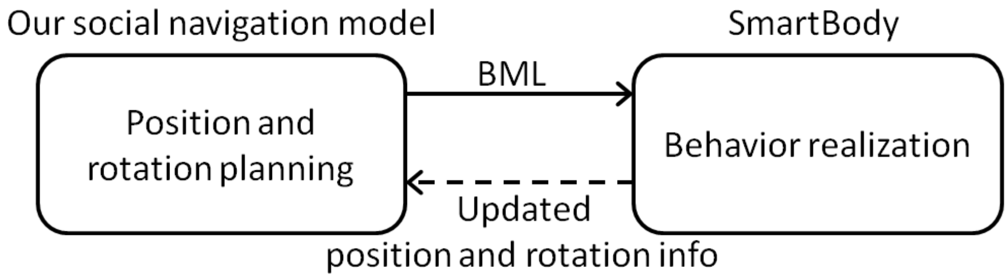


Figure 4.2. The run-time two-stage spatial behavior generation process in our implementation

As our model continuously evaluates the interestingness and monotony scores of groups in the scene, this closed loop of social spatial behavior planning and realization continues its execution until the end of the simulation. In the following sections we detail our social spatial behavior planning algorithm as well as the process of initializing parameters of the model and the scene.

4.4.1. Social Spatial Behavior Planning Algorithm

Social spatial behavior planning algorithm is the main component that realizes our social navigation model. Given an initial social scene with several virtual groups, a subject character, and a set of parameter values to configure the model, the social spatial behavior planning algorithm continuously generates BML commands for navigating the subject in the virtual scene. We postpone explanation of our configuration and initialization process to the next section and start by describing our social spatial behavior planning algorithm here. It is worth mentioning that our algorithm exclusively plans the next position and rotation of the subject, and for path planning and obstacle avoidance we rely on the capabilities of SmartBody.

We implemented our social spatial behavior planning algorithm as a Python module (consisting of 17 Python scripts) that uses SmartBody's higher level Python API and is run by its built-in Python engine. The Python API provides us with access to SmartBody's internal objects that represent our virtual characters, events raised as a result of executing a BML command, and SmartBody's internal real-time clock that we use for synchronization purposes.

The social spatial behavior planning algorithm starts with obtaining the most recent position and rotation information for all virtual characters from SmartBody. Then for each group the algorithm calculates the interestingness score using equation 14. The monotony score that we use for this calculation is the collective number of times that members of a group perform an activity. Also, if the subject character has never visited any of the groups before, the interestingness of that group is the collective interestingness value of its members. Using this interestingness scores and equation 12, the social spatial behavior planning algorithm then calculates the attraction force toward each group and the group with the maximum attraction magnitude is selected as the target group for the subject to join. At this point, our behavior planning algorithm calculates the center and radius of the o-space of the target group and prepares a BML locomotion command to move the subject toward it. An example of the BML locomotion command is shown below:

```
<locomotion facing=”90” target=”100 150” velocity=”0.5;0.5;0.5”>
```

The *facing* attribute specifies the absolute rotation value in degrees that the subject should have by completion of this command, while the *target* attribute shows its absolute $[x, y]$ position. The *velocity* attribute defines the velocity of the subject's locomotion in three directions and the *manner* of locomotion is walking by default. This BML command is then sent to SmartBody for execution. In SmartBody's architecture, BML commands are executed as independent threads. Because of that, on the next tick of the clock after sending the BML command, our social spatial behavior planning algorithm can check for the updated position and rotation information of the subject and determine if it has reached the target group. While the subject is still on its path toward the target group, the behavior planning algorithm keeps calculating the attraction force towards all groups to make sure the selected target group is in fact the most attractive group for the subject. In case another group with a stronger attraction force is found, the behavior planning algorithm immediately retargets the subject to the new group.

When the subject gets close enough to the target group so that the group members are detectable in the subject's social area, the repulsion force is calculated. From this point forward, the summation of the attraction and repulsion vectors is used to generate BML commands to navigate the subject for the rest of the path. Finally, when the subject reaches the circumference of the o-space of the target group, SmartBody raises an event to indicate the end of execution of the last BML command. This is when the subject takes an idle position and stays in the group until its leaving threshold is reached.

While the subject is in the group, our social spatial behavior planning algorithm uses interest model of equation 14 to update interestingness score of the current group. It also calculates the leaving threshold using a combination of the subject's characteristics and the interestingness scores of other groups, as shown in equation 15.

$$I_{min_{target}} = c + \frac{\beta}{n-1} \sum_{g \neq target} I_g\left(t, T_{max_B}, m_B, t, T_{max_R}, m_R\right) \tag{15}$$

In equation 15, c is a constant value which represents the subject's characteristics influencing how quickly it gets bored of interactions. Parameter β is the weight of the environment's effect on the leaving threshold, n is the total number of groups in the environment and the rest is the average interestingness score of all groups excluding the current group of the subject.

As soon as the interestingness score of the current group drops to leaving threshold, our social spatial behavior planning algorithm starts to navigate the subject out of its current group and toward the most interesting group out in the environment. This run-time process is illustrated as a flowchart in Figure 4.3.

We developed 17 Python scripts that together implement the flowchart of Figure 4.3. These scripts include separate classes encapsulating information of the entire testcase, groups, subject, members, permanent properties of members (the sources of members' interestingness) and temporary properties of members (i.e., activities they perform). Also there are a set of scripts that manage the information flow between our classes. Below is a list of major scripts and classes with their responsibilities.

- Simulation runner script: loads the testcase, initializes the scene, runs the timer script, sets up SmartBody's steering managers for characters and starts the simulation
- Testcase loader script: retrieves testcase data from file and creates testcase instance

- Scene initializer script: creates subject character and group members, positions all virtual characters within the scene and configures the camera
- Configuration handler script: configures parameters of our model from a configuration file
- Timer script: synchronizes our simulation with internal clock of SmartBody, updates interestingnesses of groups (by propagating the message to testcase), calculates leaving threshold of subject and checks if the subject should join a group and continuously calls navigator script
- Navigator script: calculates attraction force toward each group, selects target group, calculates repulsion force, generates BML locomotion commands and finally sends the BML commands to SmartBody for execution
- Testcase: The object that acts as a container for all groups and the subject and propagates messages to them
- Groups: A set of group objects that contain group members. A group object is in charge of calculating its center, propagating messages to its members, calculating its interestingness and monotony scores and keeping track of the subject leaving and joining it
- Members: A set of member objects that have access to their interestingness and level of activity information. A member object also provides access to its position and rotation information in real-time
- Subject: The object that is in charge of providing state information to the navigator algorithm as well as partially calculating leaving threshold. Like a member object, subject also provides access to its position and rotation information in real-time
- Logger: The object responsible for logging the positional data and interestingness scores generated by the social spatial behavior planning algorithm, to be used for visualization purposes

The important run-time communications between these components are illustrated in Figure 4.4. For the sake of readability, Figure 4.4 does not show all communications between components and thus is not a complete sequence diagram of the system. In the next section, we focus on the initialization phase of our implementation and describe parameter configuration in our system, testcase file structure and testcase designer apparatus.

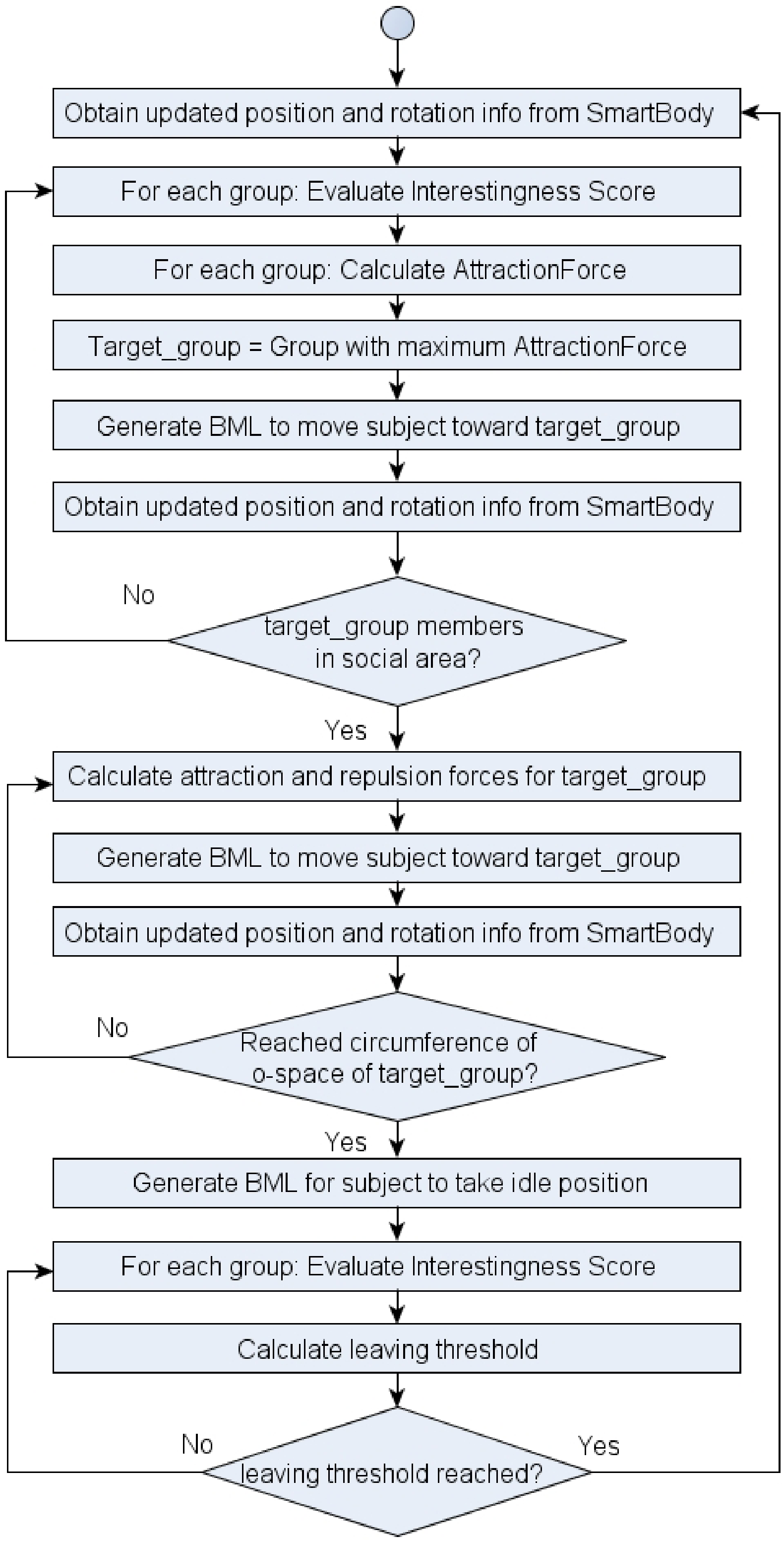


Figure 4.3. The execution time flowchart of our social spatial behavior planning algorithm

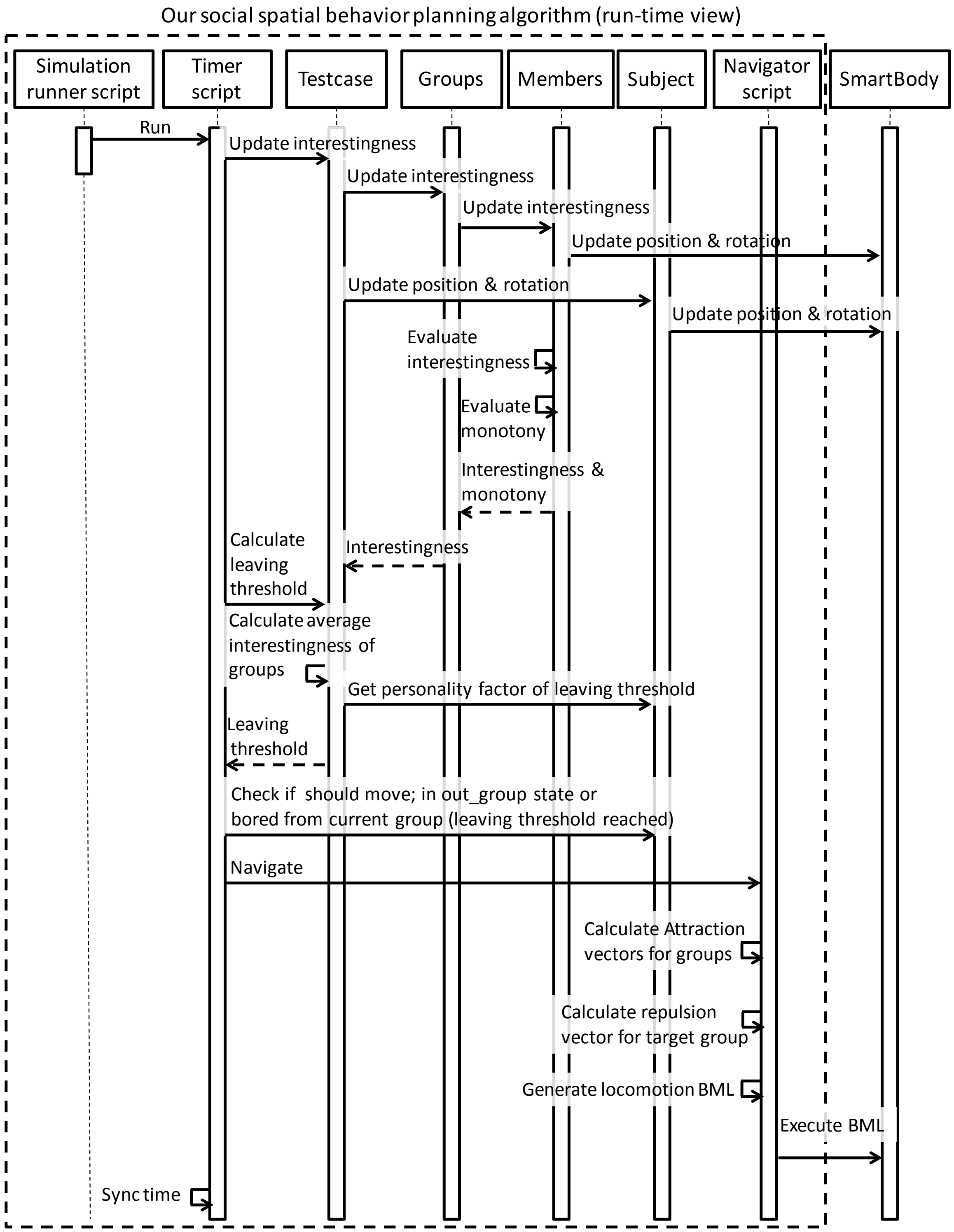


Figure 4.4. Pseudo sequence diagram of communications between major components of our social spatial behavior planning algorithm in run-time

4.5. Initialization Process of Our Social Spatial Behavior Planning Algorithm

In the previous section we described our social spatial behavior planning algorithm in run-time. However, none of the mentioned functionalities can be achieved if the model is not properly initialized with configuration parameters. In this section we describe the initialization process and the data files and tools we developed to facilitate it.

There are two files containing initialization information for our social spatial behavior planning algorithm: testcase information and parameter configuration. Testcase information file is an XML file which contains the initial information about the scene of the simulation, whereas parameter configuration file contains parameter values to be used in interest model and social force field calculations. We first demonstrate the process in which these two files are used for initialization of our system, and then provide detailed explanations on their contents.

Our simulation runner script starts by running the testcase loader which is in charge of loading the grouping, position, rotation and other information about the scene from the testcase XML file. After reading the file, the loader uses the extracted information to create an internal representation of each object in the scene such as subject and group members. These internal representations are later linked to their corresponding 3D virtual characters in SmartBody by the scene initializer script. Using the internal representations of the objects, the scene initializer creates the corresponding virtual characters, sets the proper meshes for their appearance and positions them in the scene. Each object is then responsible for calling the configuration handler to configure parameters of the model that it uses. Finally, each member object uses its activity information to generate a set of animation BML commands and sends them to SmartBody for execution. An example of the animation BML command is shown below:

```
<animation name=”cross_arms” start=”10” end=”12”>
```

The *name* attribute in this command is used to refer to one of the available pieces of animations in SmartBody and *start* and *end* are the synchronization constraints. *Start* specifies the time of starting the animation in seconds, with the time of starting the simulation being its origin. In a similar manner, *end* shows the time of ending the animation. As a result of executing this command, the corresponding character will start to cross its arms at the 10th second of the simulation and finishes crossing them at the 12th second. Figure 4.5 summarizes the initialization process of our behavior planning algorithm. The communications shown in this illustration happen immediately before those shown in Figure 4.4.

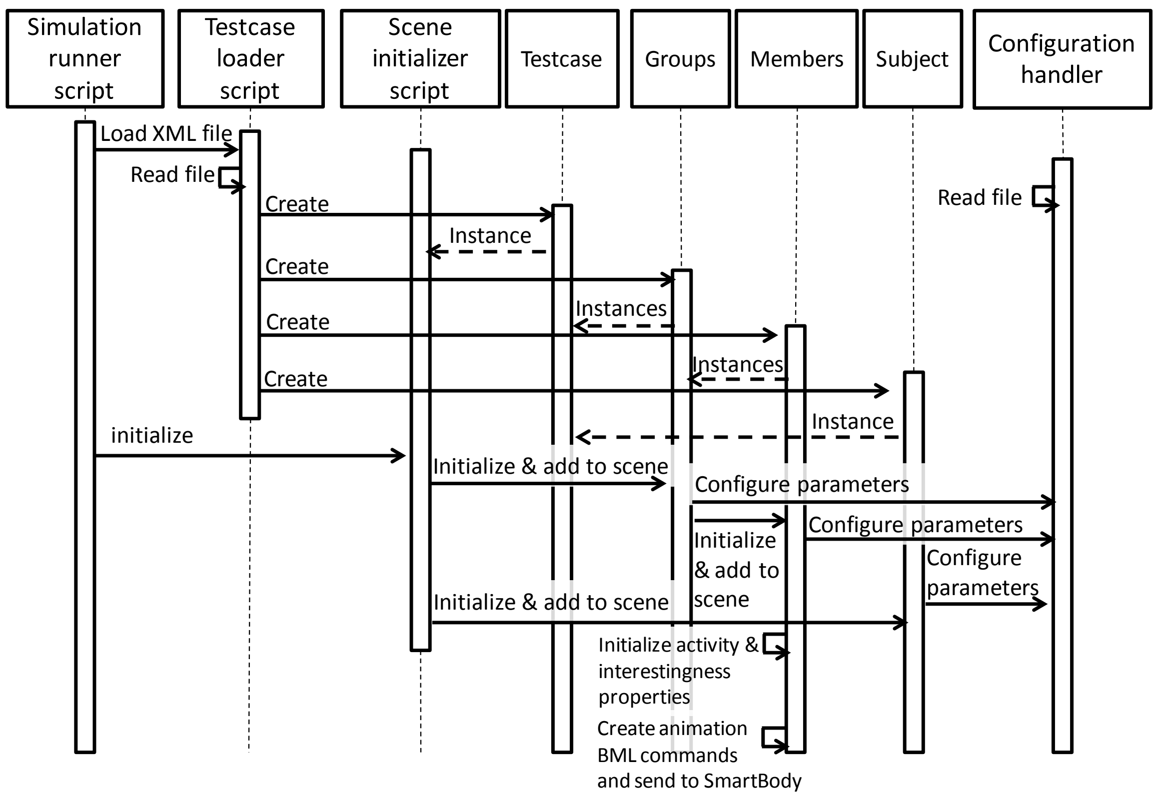


Figure 4.5. Initialization process of social spatial behavior planning algorithm

In the following sections we describe the structure of the testcase and configuration files used in the initialization process.

4.5.1. Initial Scene Information as an XML File

The information that specifies the initial scene in every simulation is contained in the testcase file. This is an XML file having initial position and rotation information for each character, as well as a nested structure for elements that show their relationships; for example, interestingness and activity properties of a group member are listed as nested elements under that member. At the root of a testcase file is the *Testcase* tag with a *name* attribute. There is also a *Description* tag for the *Testcase* that can be used for commenting purposes. Nested under the *Testcase* are *Subject* and *Groups* tags. *Subject* has a *name*, *locX* and *locY* to specify its initial position in the scene, *rotation* for its initial rotation value, and finally the radiuses of its personal and social areas in *personalAreaR* and *socialAreaR* respectively. Under *Groups* comes a set of *Group* tags with *name* attributes and their members. Each *Member*, like the *Subject*, has *locX*, *locY* and *rotation* attributes as well as a set of *Properties*. *Properties* are the sources of interestingness score of the member and its activity level. A member can have any number of *PermanetStatuses* that are representations of interesting attributes of that member for the subject. For example, being the subject's boss can be represented as a *PermanetStatus.* Each *PermanetStatus* has a *value*, a *maximum value* and a *weight* that help evaluating it. To evaluate interestingness of a member we use equation16.

$$Interestingness_m = \sum_{permanentStatuses_m} weight \times \frac{value}{maximumValue} \tag{16}$$

In addition to *PermanentStatus*, a member can also have any number of *TemporaryProperties* which are indications of activities of a group member within the group. Besides the *value*, *maximum value* and *weight*, a *TemporaryProperty* also has temporal aspects shown in its *startTime* and *endTime.* In our social spatial behavior planning algorithm, we use the number of *TemporaryProperties* of a member as its level of activity (monotony score). Also we represent each TemporaryProperty with an animation that starts and ends at *startTime* and *endTime* respectively. An example of the testcase XML file is shown in Figure 4.6. After completion of scene initialization, the configuration handler script initializes parameters of the model from a configuration file. The parameters initialized in this process are explained in the next section.

```
▼<Testcase name="Interest Model">
  ▼<Description>
     This testcase shows the effect of interest model
     parameters on spatial behavior
   </Description>
   <Subject name="subject" locX="253" locY="226"
   rotation="-90" personalAreaR="120"
   socialAreaR="200"/>
  ▼<Groups>
    ▼<Group name="InterestingMonotone" color="#2F313C">
      ▼<Members>
        ▶<Member name="InterestingMonotone_member0"
         locX="335" locY="76" rotation="174">...</Member>
        ▼<Member name="InterestingMonotone_member1"
         locX="367" locY="60" rotation="97">
          ▼<Properties>
             <PermanetStatus name="Boss" value="7"
             maxValue="10" weight="1"/>
             <TemporaryProperty name="Speak" value="2"
             maxValue="10" weight="0" startTime="23"
             endTime="30"/>
           </Properties>
         </Member>
        ▶<Member name="InterestingMonotone_member3"
         locX="399" locY="78" rotation="18">...</Member>
        ▶<Member name="InterestingMonotone_member4"
         locX="394" locY="121" rotation="304">...
         </Member>
       </Members>
     </Group>
    ▶<Group name="BorigMonotone" color="#DA2113">...
     </Group>
    ▶<Group name="BoringMultitone" color="#788B3A">...
     </Group>
    ▶<Group name="InterestingMultitone"
     color="#158833">...</Group>
   </Groups>
 </Testcase>
```

Figure 4.6. A sample testcase xml file for initializing the scene of simulation

4.5.2. Configuring Parameters of the Model

Our model parameters should be set for each simulation, and this is achieved via a configuration file. This file, called config.ini, contains four sections corresponding to the different scopes in our behavior planning algorithm. Under each section, related parameters and values are listed for the current simulation. Notice that in this implementation we partitioned the space of possible monotony scores to high and low using a threshold value. Depending on being low or high in monotony, groups use different values for calculations of interest model. Below is the description of parameters of our social spatial behavior planning algorithm.

- TestcaseFileInfo
  - Dir: The absolute address of the directory containing testcase XML file
  - TestcaseName: Name of the file within the above directory that contains our initial scene information

- Timer section
  - SimulationDuration: Specifies how long the simulation is executed and relevant data is collected; measured in seconds and should be an integer >= 0
  - SynchScale: Defines how many ticks of the internal clock of SmartBody should pass before subject's information about the virtual room is updated. Should be an integer >= 1. If set to 3, subject receives information about environment every 3 seconds.

- Navigator
  - MaxPerceivableDistance: Same as D_{max} in equation 11, shows the maximum distance perceivable by the subject in calculating psychological distance; measured in centimeters
  - MappingRateFromPhysicalToPerceivedDistance: Same as r in equation 11, defines the control parameter for mapping physical distance to psychological distance
  - Velocity: Velocity of movement to be used in generating locomotion BML commands for the subject

- Interestingness
  - HighToLowMonotonyThreshold: the Threshold used to partition monotony scores to low and high. If the collective number of temporary properties of members of a group is less than this threshold, the group is considered high in monotony.
  - HighMonotonyR: Same as m_B in equation 14 for a group with high monotony; this parameter shows the rate of losing interest in interest model

- LowMonotonyR: Same as m_B in equation 14 for a group with low monotony; this parameter shows the rate of losing interest in interest model
- Tmax: Same as $\mathrm{T}_{\mathrm{max}_\mathrm{B}}$ in equation 14; this parameter is the maximum time it takes the subject to completely lose interest in a group
- RecoveryTmax: Same as $\mathrm{T}_{\mathrm{max}_\mathrm{R}}$ in equation 14; this parameter is the maximum time it takes the subject to recover interest in a group to its original interestingness value
- HighMonotonyRecoveryR: Same as m_R in equation 14 for a group with high monotony; this parameter shows the rate of recovering interest in interest model
- LowMonotonyRecoveryR: Same as m_R in equation 14 for a group with low monotony; this parameter shows the rate of recovering interest in interest model
- LeaveThreshold: Same as constant c in equation 15; this parameter is the personality factor in calculation of leaving threshold. This is a representation of subject's personal characteristics that influence how quickly it gets bored of interactions.
- EnvironmentalEffectWeight: Same as parameter β in equation 15; this parameter is the weight of environment's effect on the leaving threshold

Values provided for these parameters configure our social navigation model for the simulation of each testcase.

Given the configuration and the testcase XML files, we can completely initialize our behavior planning algorithm as described in this chapter so far. However, manually creating and maintaining an XML file containing over a few group members is an exhaustive task. Thus, to facilitate the creation and maintenance of testcases, we developed a testcase designer apparatus which we describe in the next section.

4.5.3. Testcase Designer Apparatus

Our testcase designer apparatus is a helper tool that lets the user graphically design the initial scene for a testcase. Figure 4.7 shows a snapshot view of the testcase designer. In the left panel there are buttons for creating a new testcase, adding new groups to the scene and saving and loading the testcase files. Also there is a property grid view in the left panel that shows the properties of the object selected in the right panel. For example, by clicking on a group member and selecting it in the right panel, position and rotation information for that member appear in the property grid on the left.

By clicking on the *add group* button on the left, a new group can be added to the scene. The name of the new group shows up in the top left corner of the right panel. After selecting the name of that group, the user can activate *Member mode* on the left and then click on any part of the right panel to place a new member for that group. The rotation value of the new member can also be set via the property grid. Position of existing members can be modified by dragging and dropping. By adding the third member to each group, the center and envelope of that group are automatically calculated based on equation 6 and is graphically shown to the user.

Finally, by switching to *subject mode* on the right, the user can place the subject in the scene. There are two circular areas shown around the subject; these are the personal and social areas of subject and their radiuses can be edited in the property grid while the subject is selected.

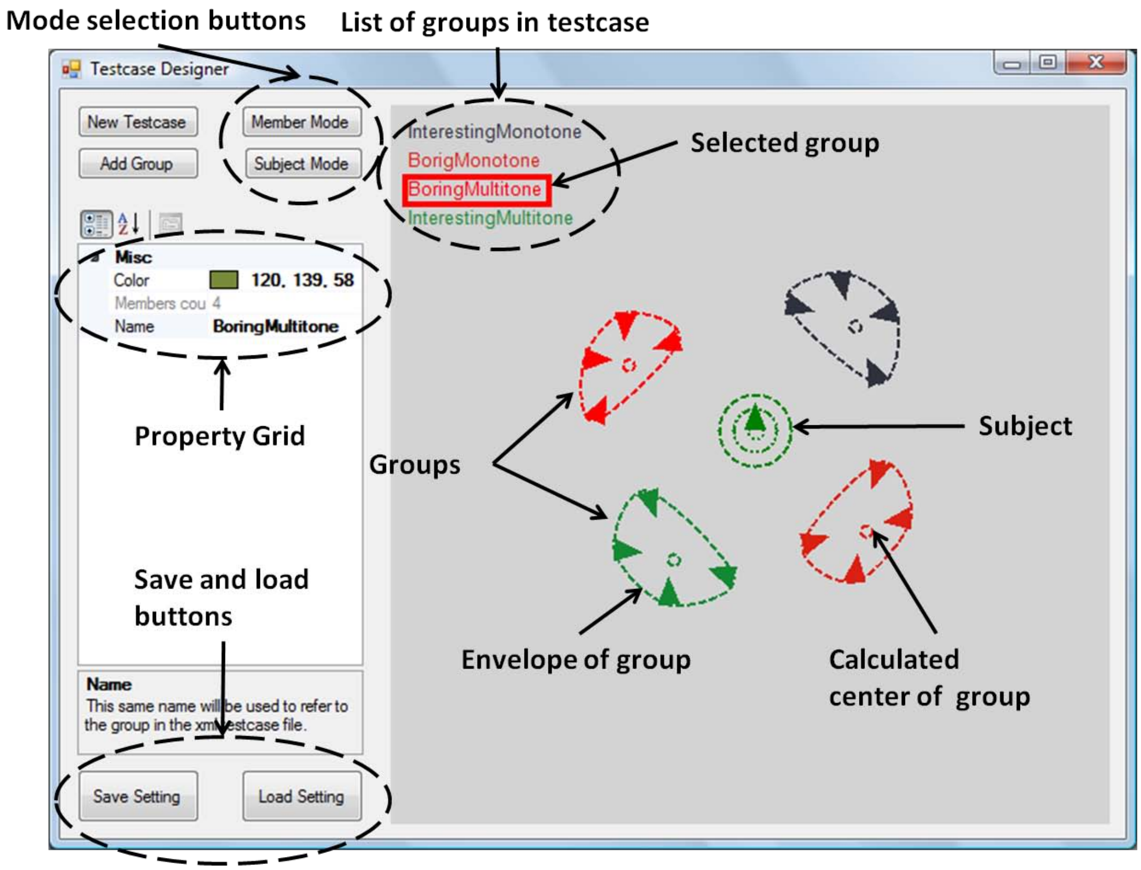


Figure 4.7. ***A snapshot of our testcase designer apparatus***

By saving this graphical testcase, our testcase designer converts the graphical information to XML format and this XML result can later be used to initialize the social spatial behavior planning algorithm. Figure 4.8 shows a summary of our initialization process.

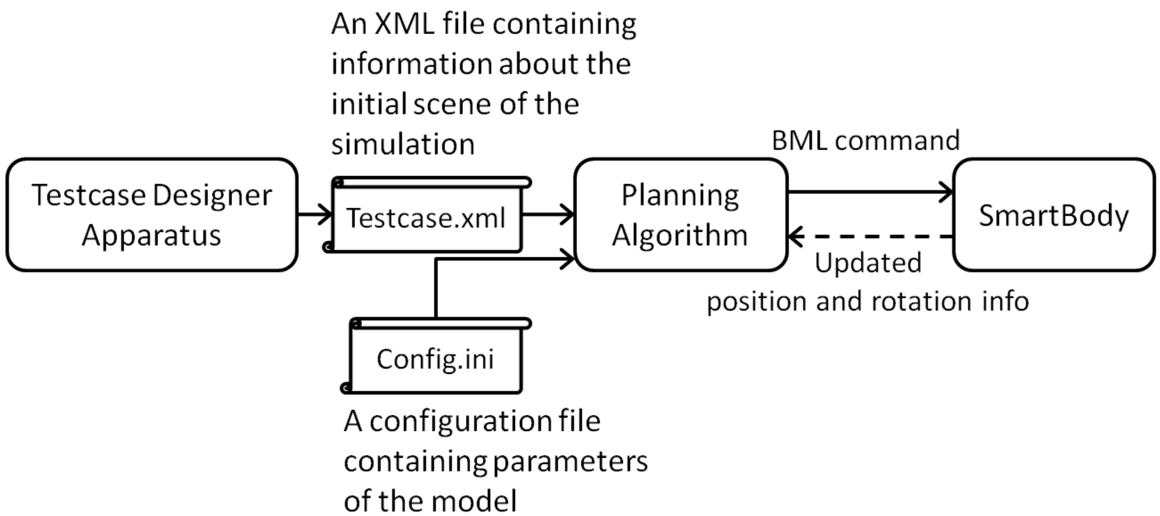


Figure 4.8. An abstract view of the initialization process emphasizing on the roles of components

4.6. Summary

In this chapter we described our implementation of the social navigation model we proposed in chapter 3. We used a two-stage spatial behavior generation in our implementation that breaks behavior generation process into planning and realization parts. In the backend we employed SmartBody platform as the animation and behavior realization engine, while in the frontend we developed our own social spatial behavior planning algorithm to plan the spatial behavior. We described how the planning algorithm adopts our model of interest to calculate the next position and rotation information for the subject in real-time. Based on this information, the social spatial behavior planning algorithm then generates locomotion BML commands and sends them to SmartBody for execution.

We also presented the initialization process of our behavior planning algorithm in which the initial scene information and model parameters are set. To initialize the scene we designed an XML structure containing position, rotation and object relationship information, and through an XML file, sent this information to the behavior planning algorithm. Also to configure model parameters for each simulation, we created a configuration file that contains parameters for the interest model as well as psychological distance calculations and simulation synchronization. Lastly, in order to facilitate the generation and maintenance of our XML files, we developed a testcase designer apparatus. This tool provides the users with a graphical means of designing the initial scene for their simulations using our social spatial behavior planning algorithm. Users can graphically create groups, add members to the groups, add subject to the scene, edit position and rotation of both subject and members and save this information as an XML file through our testcase designer. In the next chapter, we describe four testcases we simulated using this implementation of our model.

5. Testcases

5.1. Overview

To demonstrate the social spatial behavior generation capabilities of our model, we simulated a series of testcases using the behavior generator system we developed in chapter 4. These simulations included different arrangements of the social scene and through each simulation we studied the actual effect of the forces and parameters of the system, as listed in section 4.5, on the generated spatial behavior.

In all the presented testcases we use the appearance of the group members as an indication of their initial interestingness score. Also to visualize the monotony scores of members, we employ a set of animation snippets showing different activities. In the initialization process and right before creating the virtual character for each member, our scene initializer script performs an initial evaluation of the permanent statuses of the member. Based on the value of the result, it selects a different character type (with a different mesh) to create the member. At the time of writing this thesis, SmartBody contains six default character types, two of which are introduced just recently. These characters are shown in Figure 5.1 (From left to right: Rachel, Billford (recently added characters), Utah, Elder, Doctor and Brad).

(a) (b)

Figure 5.1. ***Six default character types of SmartBody. (a) recently introduced characters: Rachel and Billford, (b) initial characters: Utah, Elder, Doctor and Brad from left ro right***

To display activities of each character, we used an animation snippet for each temporary property it has. The animation snippet starts and ends at the start and end times of the corresponding temporary property.

Assuming that Doctor, Brad and Utah represent members of high, medium and low interestingness to our subject, one can observe four types of groups in Figure 5.2. Active members show groups of low monotony that we refer to as dynamic groups, while groups with more Doctors are our more interesting groups. Therefore, from top to bottom and left to right there are the following types of groups in Figure 5.2: boring-dynamic, interesting-monotonous, interesting-dynamic and boring-monotonous. The differentiation between monotonous and dynamic groups is because each type uses a different set of interest model parameters in our implementation.

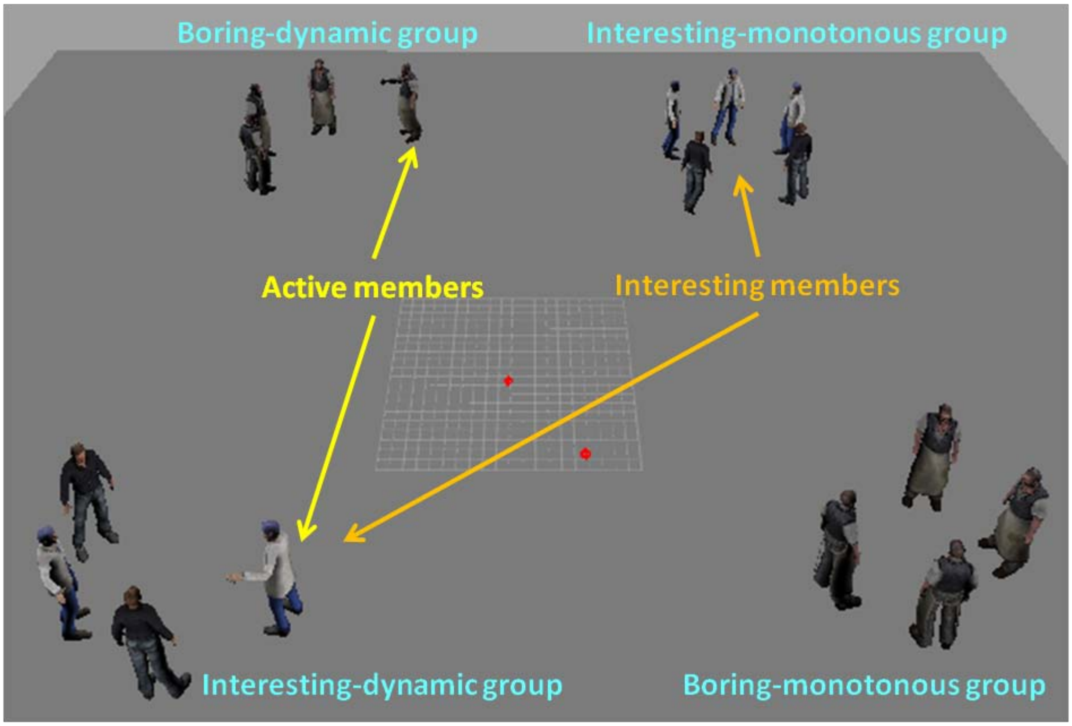


Figure 5.2. Example of a scene with four types of groups

In the upcoming sections we describe four testcases we simulated from simple to complex scenarios. The first two testcases are about the subject joining a group whereas testcases 3 and 4 show the spatial behavior our model generates in more complex scenarios including four groups. In testcases 1 and 2, we show the effectiveness of attraction and repulsion forces in navigating the subject toward a group and properly positioning it within the group. Testcase 3 looks at the influence of parameters of our interest model on the pattern of trajectory of subject and finally in testcase 4 we show how different values of personality factor of leaving threshold can regulate the time that the subject spends in each group. For all these testcases, the xml scene information, configuration file and video recording of the resulting behavior are available online at http://ivizlab.sfu.ca/research/SocialCharacterThesis/.

5.2. Testcase 1: Attraction Force

The goal of this testcase is to demonstrate the functionality of the attraction force in our social force field. In this simulation, the subject's trajectory shows the path in which the attraction force navigates the subject. According to F-formation theory (Kendon, 1990) this path ends on the circumference of the o-space of the group. Figure 5.3 (a) illustrates the arrangement of the initial scene used for this simulation and designed by our testcase designer tool. Figure 5.3 (b) shows a top-view snapshot of the simulation result after the subject completely joined the group and took an idle position. Note that the solid yellow line shows the trajectory of the subject and the red line-segment at its end is the last attraction vector generated by our navigator. Also, the orange dashed line is added after the snapshot is taken, to approximately show the o-space of the group. The green arrows, like the trajectory line and the red vector, are parts of the original snapshot to visualize the direction of group members. Visualizing trajectories and directions is a feature of the sbm-fltk viewer of the SmartBody that we use for the simulations of this chapter.

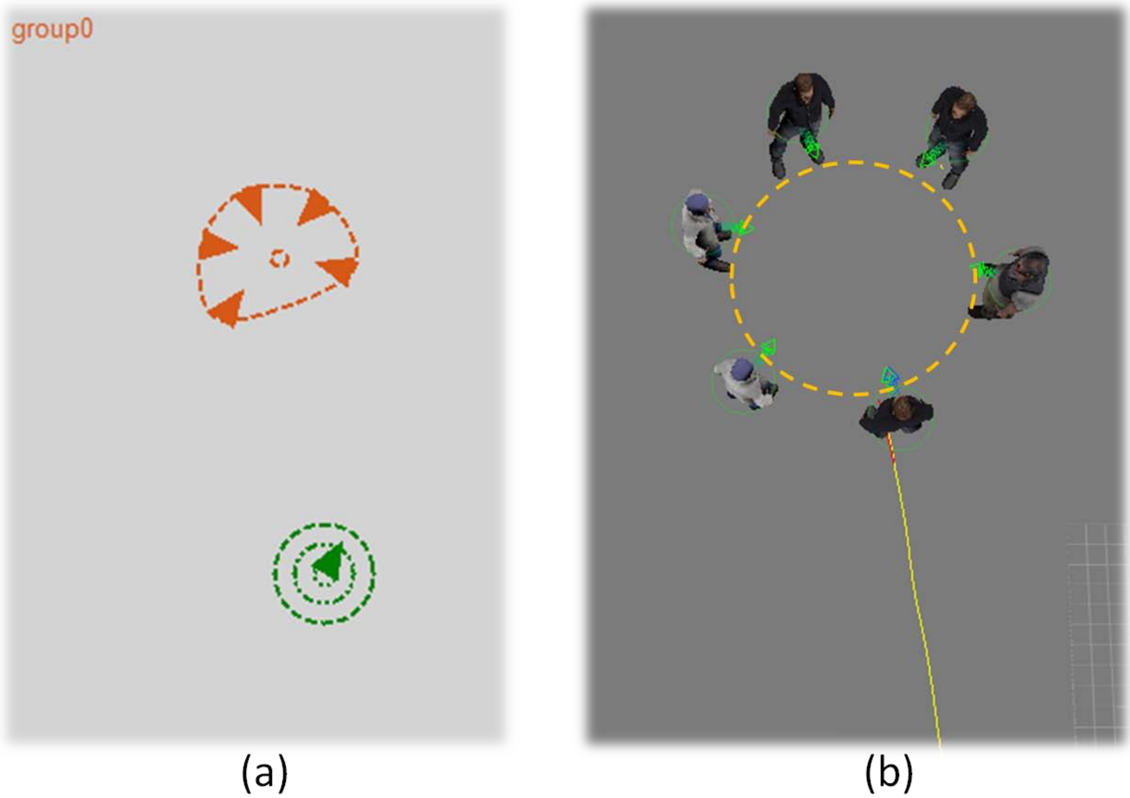
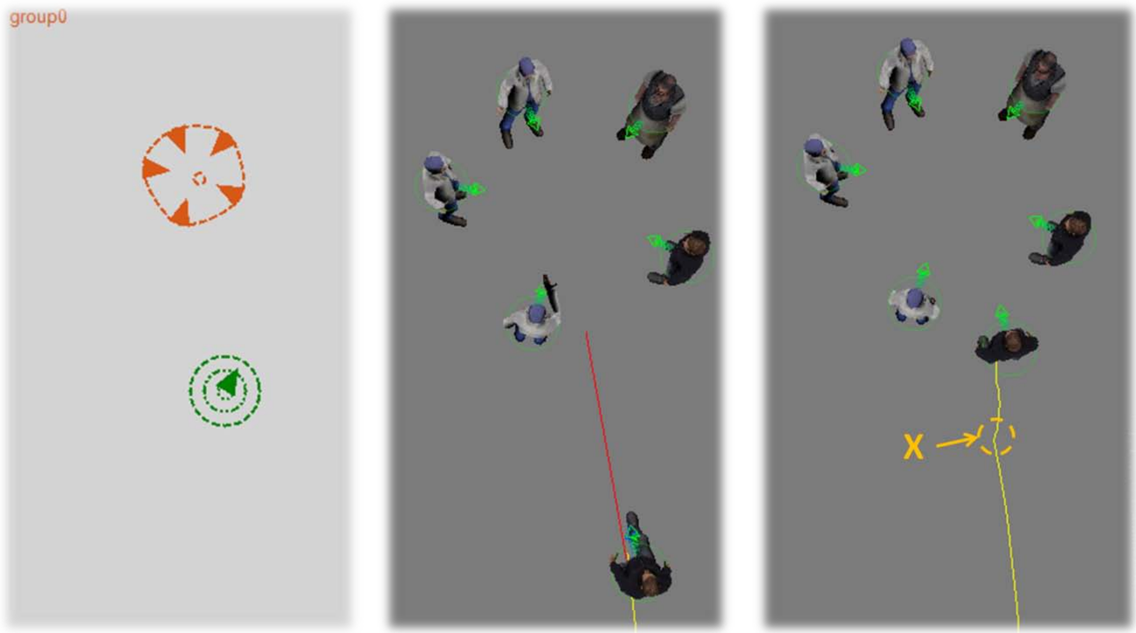


Figure 5.3. Attraction force testcase: (a) the initial scene of the testcase; (b) snapshot of the simulation result right after the subject joins the group

Looking at Figure 5.3 (b) one can tell that the attraction force navigates the subject in a smooth path toward the group and the last attraction vector points to the proper position on the o-space of the group. The subject's final direction is correctly set toward the center of the group and finally, the subject has ended up in a position that gives the whole group a roughly circular shape, providing direct, equal and exclusive access to conversation for all group members. According to the F-formation theory, we believe this generated behavior is a valid human-like behavior. In the next testcase, we look at the effect of our repulsion force in the subject's navigation.

5.3. Testcase 2: Repulsion Force

In this simulation we show the functionality of our repulsion force. Unlike the previous testcase, arrangement of the group members in this testcase does not allow for the subject to be positioned on the circumference of the o-space of the group without its personal space being violated. Remember that the o-space of the group, according to F-formation theory (Kendon, 1990), is the circular area defined by the group members which provides direct, equal and exclusive access to conversation for all members. For this simulation, radiuses of social and personal areas of the subject are set to 150 and 200 centimeters. It is worth mentioning that the height of the subject character is 204 centimeters, so that the reader can use it as a rough visual measure of distances.



(a) (b) (c)

Figure 5.4. ***Repulsion force testcase: (a) the initial scene of the testcase; (b) snapshot of the simulation result early after subject starts to move; (c) snapshot of the simulation result right after the subject joins the group. Point X is where the repulsion force gets activated***

Figure 5.4 (a) shows the initial design of the scene for this simulation. In Figure 5.4 (b), the subject has just started to move toward the group and all members of the group are located outside its social area. The red line-segment illustrates the attraction vector that is used in this stage of movement to navigate the subject toward the group. One can tell that the destination chosen by the attraction vector, although on the circumference of o-space, is too close to the Doctor on the right. Unless the repulsion force adjusts this vector, the situation will result in the violation of the subject's personal space. Lastly, Figure 5.4 (c) shows the snapshot of the simulation, immediately after the subject joins the group and takes on an idle position. Point X on the trajectory shows the point at which group members start to appear in the subject's social area and as a result, the repulsion force gets activated. The reader can observe that from point X forward, not only does the repulsion vector deviate the subject to the right to keep proper distance from the Doctor, it also causes the subject to stop earlier, so that its personal distance is not violated. This happens in real-life cases with humans as well; when there is not enough space around a group for a person to join, the person tends to stay back until other group members expand the o-space of the group by adjusting their positions.

Testcases 1 and 2 presented the primitive functionalities of our social force field model. In the next section we provide a complex testcase scenario where we show the effect of parameters of the interest model on the generated spatial behavior.

5.4. Testcase 3: Interest Model

Our goal in this testcase is to demonstrate the effect of parameters of interest model on the subject's trajectory and visualize if the result is human-like. The initial scene of the testcase consists of four groups that are boring-dynamic, interesting-monotonous, interesting-dynamic and boring-monotonous as shown in Figure 5.2. We use two different sets of configurations of interest model for our dynamic groups in this testcase and show the resulting trajectories. The initial scene of the testcase is illustrated in Figure 5.5.

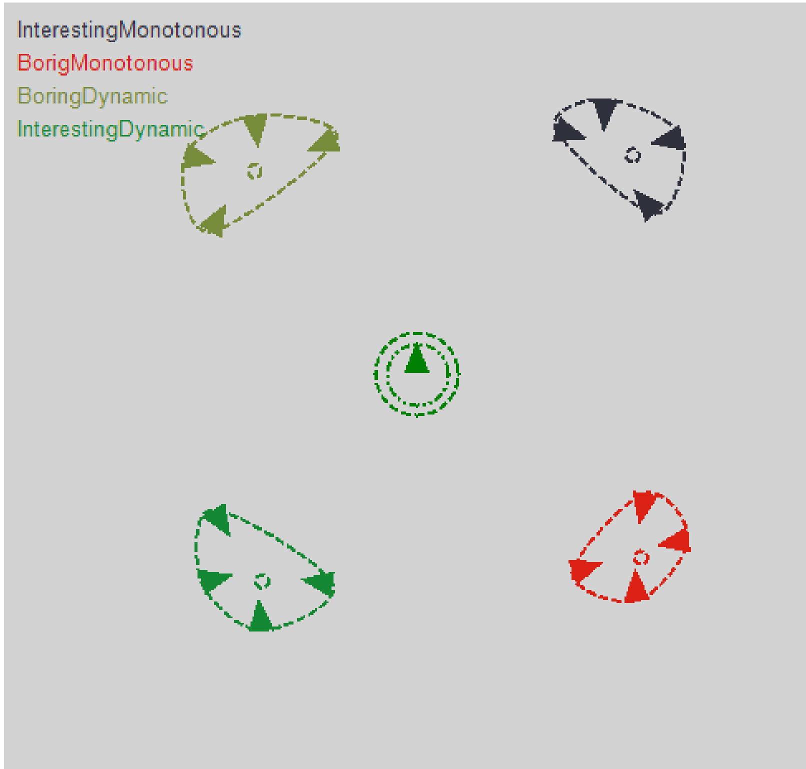


Figure 5.5. Initial scene of the interest model testcase

The testcase includes two simulations; in the first one, parameters of interest model are configured similarly for both dynamic and monotonous groups. In the second simulation though, we set a slower decay and faster recovery rate of interest for dynamic groups and visualize how this modification influences the pattern of the trajectory of the subject. Figure 5.6 illustrates the configurations used in the first simulation. For dynamic groups, we set $\mathrm{T_{max_B}} = 10$, $\mathrm{m_B} = 20$, $\mathrm{T_{max_R}} = 150$ and $\mathrm{m_R} = 320$ and for the monotonous groups $\mathrm{T_{max_B}} = 10$, $\mathrm{m_B} = 1$, $\mathrm{T_{max_R}} = 150$ and $\mathrm{m_R} = 480$ in equation 14.

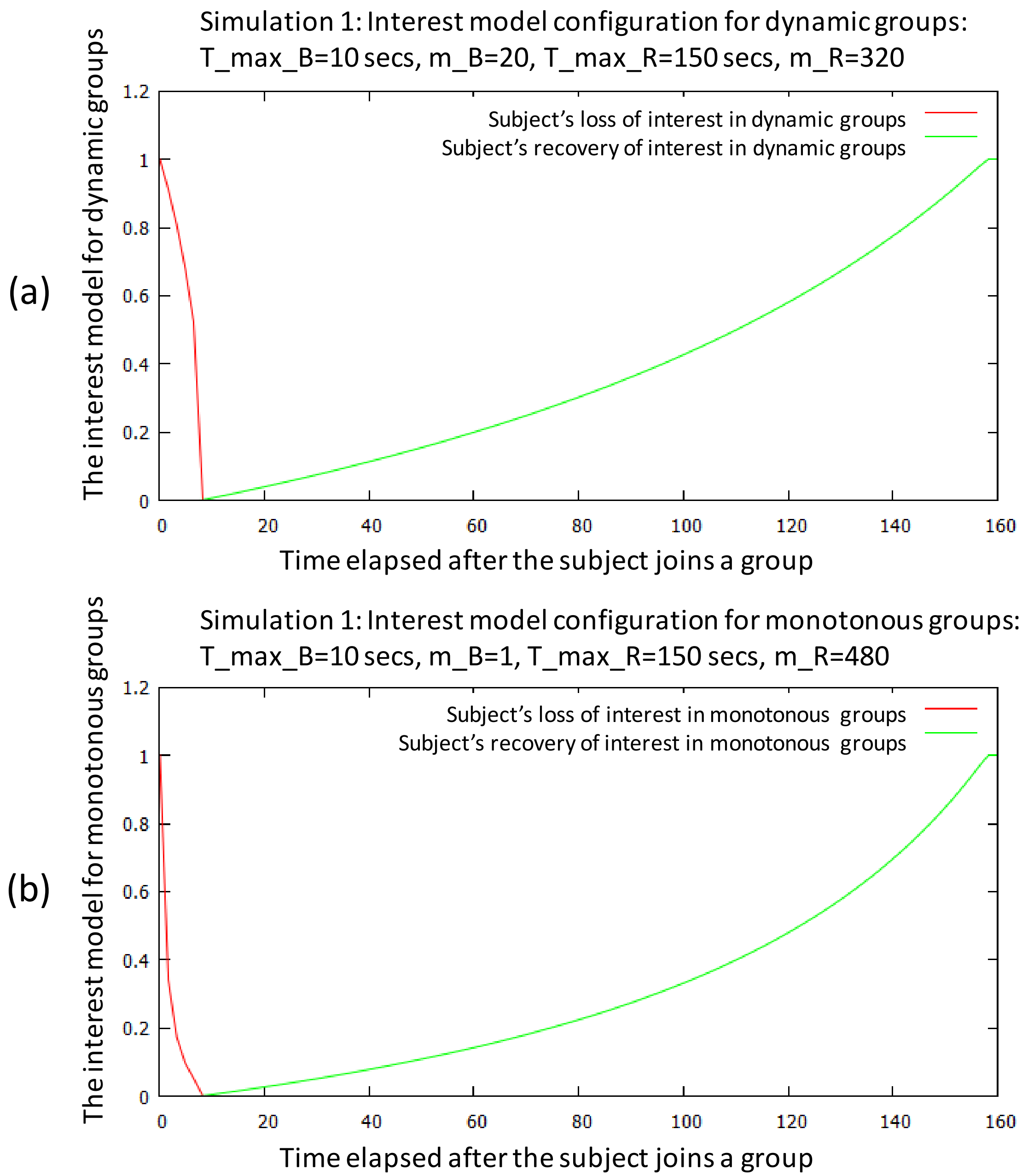
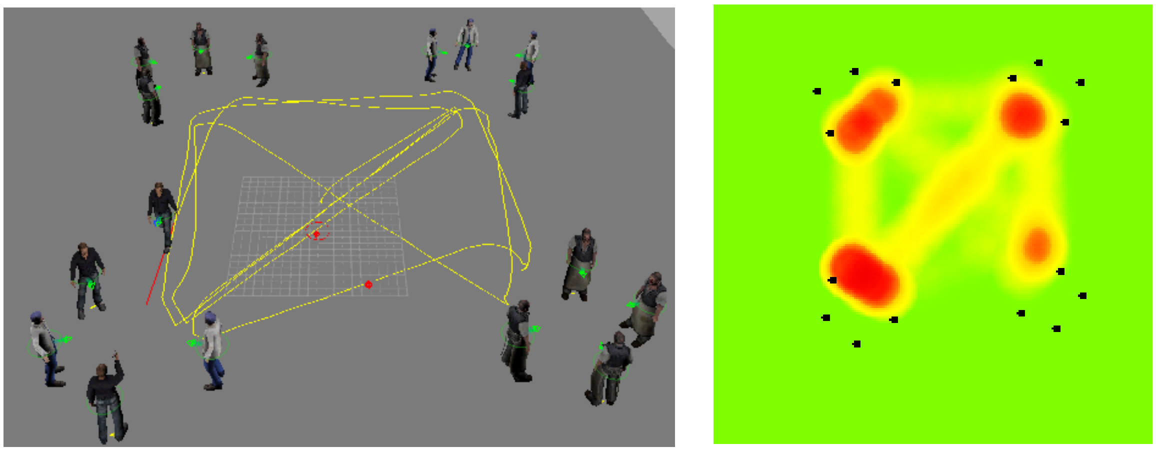


Figure 5.6. ***Interest model testcase: Simulation 1: similar interest model parameter configurations for dynamic and monotonous groups***

After 220 seconds of running the simulation, the subject's pattern of trajectory is illustrated in Figure 5.7 (a) and Figure 5.7 (b) shows a heat map view of the subject's positions during the simulation. Using the trajectory view, one can observe that the subject has visited and interacted with all four groups in a roughly uniform pattern. In addition, the heat map view shows that the subject has spent the lowest amount of time with the boring-monotonous group. Finally, the path between the two interesting groups has been walked the most according to the heat map view. This result makes sense as a human-like behavior; in a social setting, when every interaction is uniformly boring to a person, they tend to interact with every group roughly equally.



(a) (b)

Figure 5.7. Interest model testcase: Simulation 1: (a) Pattern of trajectory of subject after 220 seconds of running simulation; (b) Heat map view of the subject's positions during simulation

The dynamically changing interestingness scores of all four groups in this simulation are plotted in Figure 5.8. Each peak in this plot shows the event of subject joining the corresponding group and the order of peaks show the order in which subject has interacted with the groups.

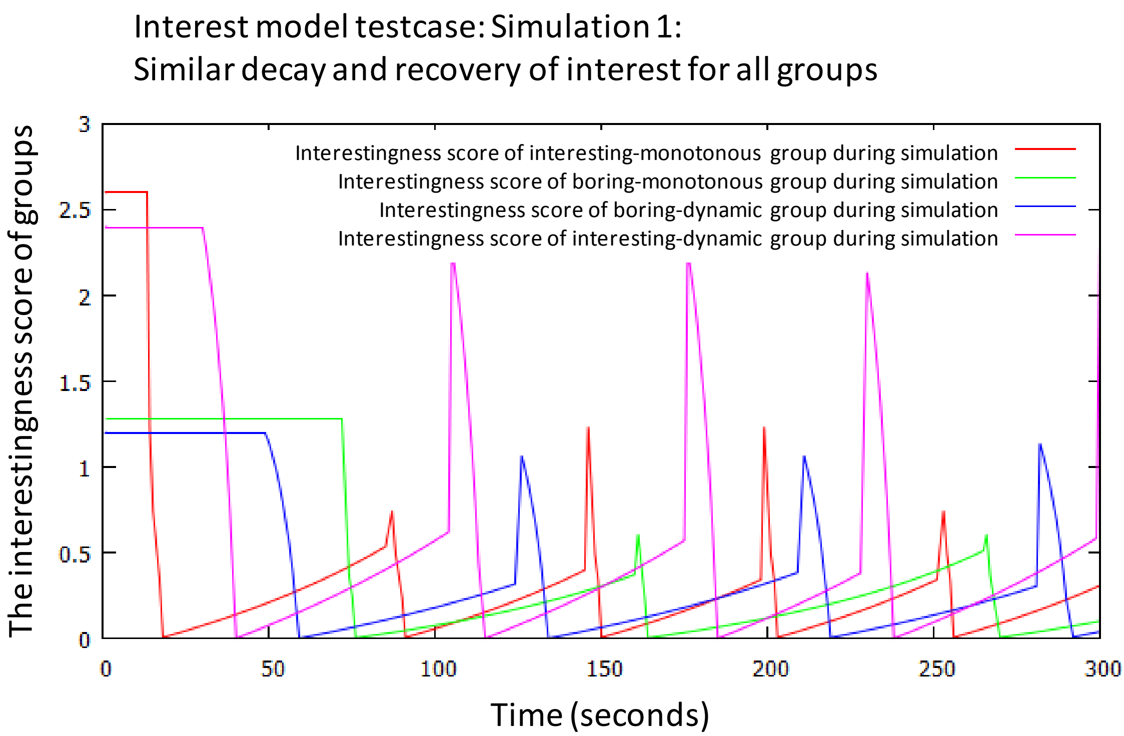


Figure 5.8. Interest model testcase: Simulation 1: Interestingness scores of all four groups plotted during simulation; similar decay and recovery of interest for all groups.

In the second simulation of the interest model testcase, we use slower decay and faster recovery parameters for the dynamic groups. Parameter configuration is as follows: $T_{max_B} = 10$, $m_B = 13$, $T_{max_R} = 100$ and $m_R = 20$ for dynamic groups and $T_{max_B} = 10$, $m_B = 1$, $T_{max_R} = 100$ and $m_R = 320$ for the monotonous groups. This configuration is illustrated in Figure 5.9.

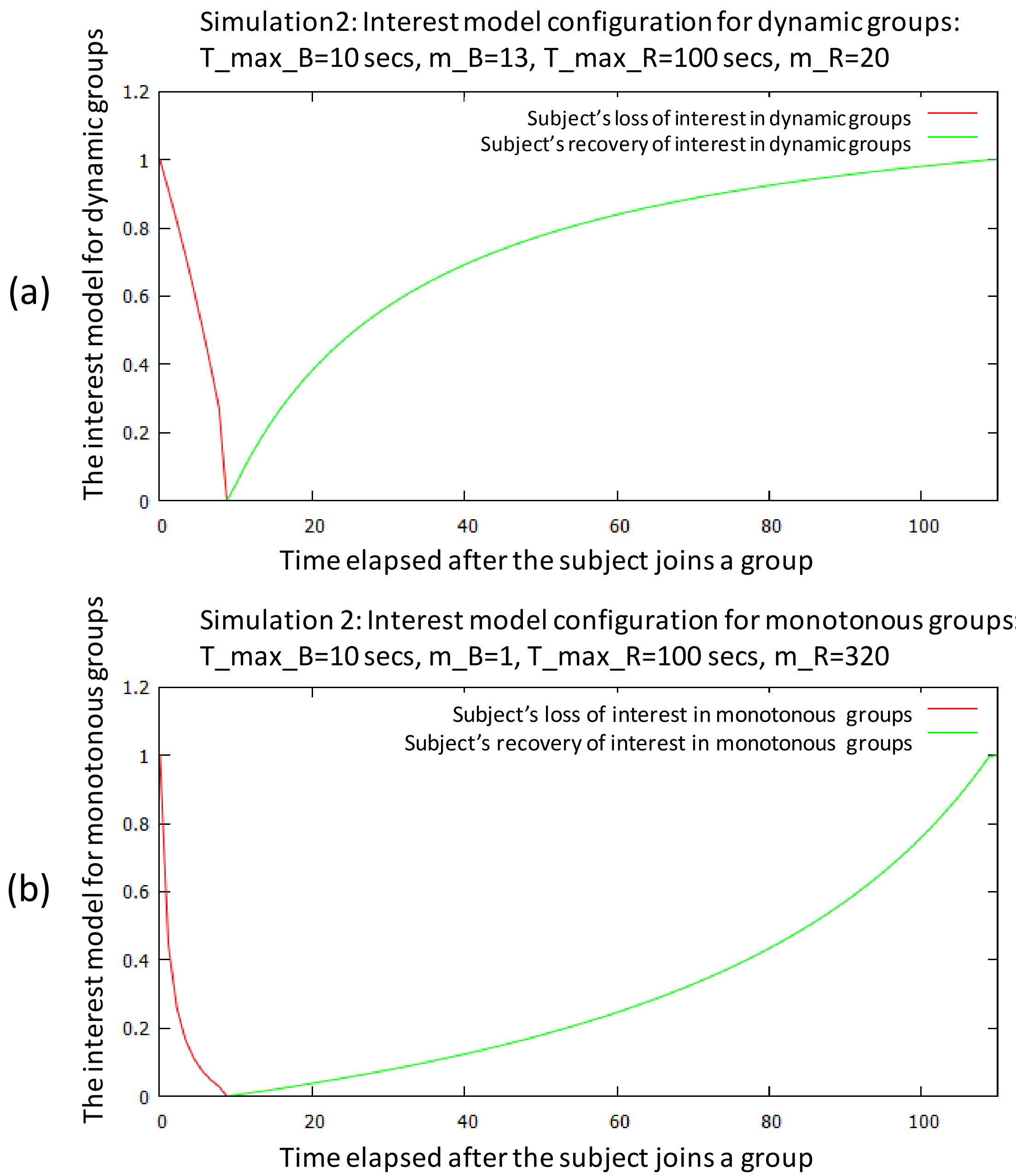
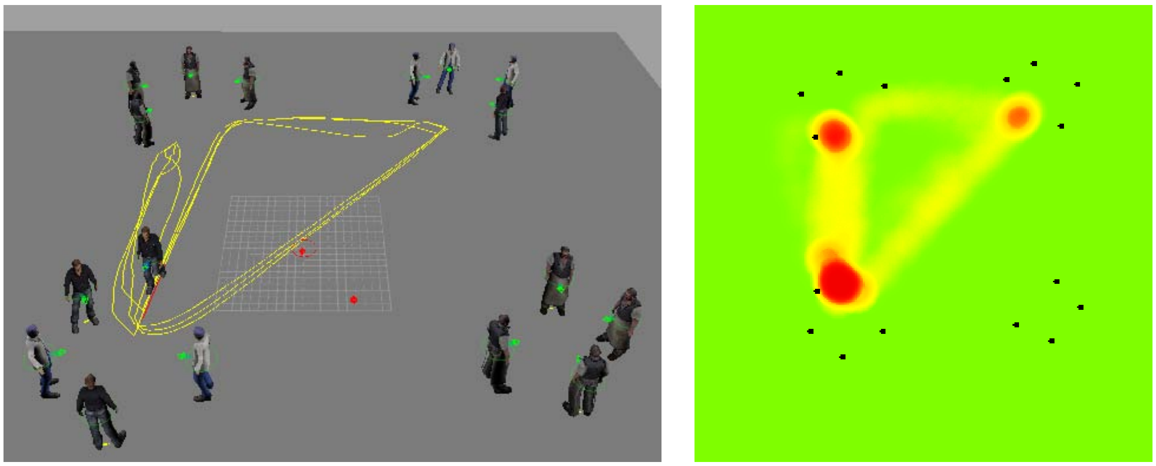


Figure 5.9. Interest model testcase: Simulation 2: slower decay and faster recovery for dynamic groups

As a result of this configuration, the subject's trajectory changes to Figure 5.10 (a). Notice that the pattern of movement is no longer uniform. Instead, the subject spends considerable amount of time going back and forth to visit dynamic groups on the left side of the scene. The interesting-monotonous group is also visited intermittently but on a lower frequency. The heat map of subject's positions shown in Figure 5.10 (b) also confirms that the major part of subject's movements happened between the two dynamic groups on the left.



(a) (b)

Figure 5.10. Interest model testcase: Simulation 2: (a) Pattern of trajectory of subject after 210 seconds of running simulation; (b) Heat map view of the subject's positions during simulation

Both of the monotonous groups on the right side of the scene use the same parameters of the interest model; but because of having a high initial interestingness score, the interesting-monotonous group is visited a few times during simulation, whereas the boring-monotonous group is left isolated. The interestingness plot of Figure 5.11 shows the reason why the boring-monotonous group is never visited by the subject; because of the fast rate of recovery for dynamic groups, at all times during the simulation, there is a group with higher interestingness score than the boring-monotonous group; thus it can never compete with other groups to attract the subject. On the other hand the interesting-monotonous group gains the interest back in a slow rate but to a higher value than the dynamic groups and that is why approximately every 50 seconds the subject is attracted to the interesting-monotonous group.

In a real-life social situation, having a preference for interacting with more active people can result in a similar spatial behavior; the person with such preference hangs out with the active groups more and spends no time with a boring inactive group. In the next section we look at the leaving threshold of our interest model and demonstrate the effect of personal characteristics of the subject on leaving threshold.

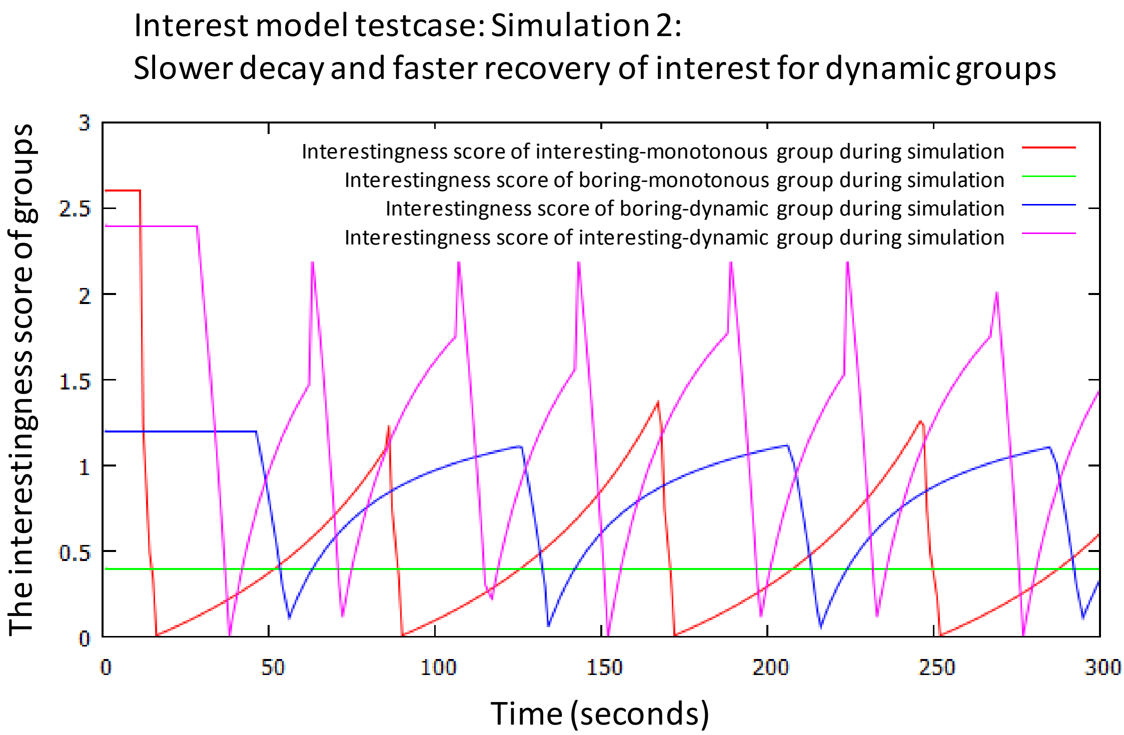


Figure 5.11. Interest model testcase: Simulation 2: Interestingness scores of all four groups plotted during simulation; slower decay and faster recovery of interest for dynamic groups

5.5. Testcase 4: Leaving Threshold

In this testcase, the effect of personality factor of the subject (parameter c in equation 15) on the leaving threshold is demonstrated. The initial scene arrangement is the same as Figure 5.5 and we ran three simulations for this testcase with c ranging from 0 to mid and maximum values; these values are set relative to the maximum initial interestingness of the groups. Knowing that the maximum initial interestingness score of groups is 2.4 and $\beta = 0$ in all three simulations, we set $c_1 = 0.0$, $c_2 = 1.2$ and $c_3 = 2.4$ for the three simulations respectively.

In the first simulation we have $c_1 = 0.0$ which reflects a subject that never gets bored of the groups. Figure 5.12 and Figure 5.13 show the result of this simulation; in Figure 5.12 the distance of the subject to the centers of all groups is plotted during the 100 second simulation while in Figure 5.13 a heat map view of the subject positions is illustrated. At any time during the simulation, the lowest line in the distances plot of Figure 5.12 corresponds to the group that the subject has been a part of, and one can see that there is no more than one such group in this simulation. That means at the beginning the subject joins the interesting-monotonous group and never leaves it afterwards. Also in the heat map view of Figure 5.13, there is no trace of the subject switching groups. A subject that never gets bored of an activity or group can possibly be an autistic person and hence, not leaving the activity can be a valid human-like behavior.

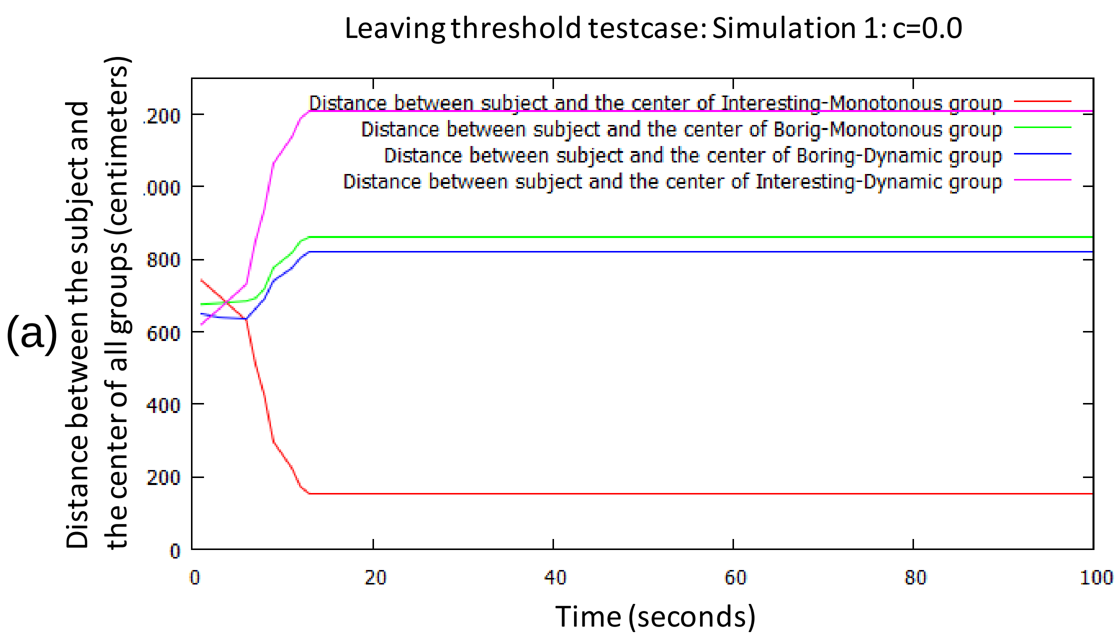


Figure 5.12. Leaving threshold testcase: Simulation 1: c = 0.0. Distance between subject and center of all groups plotted during simulation.

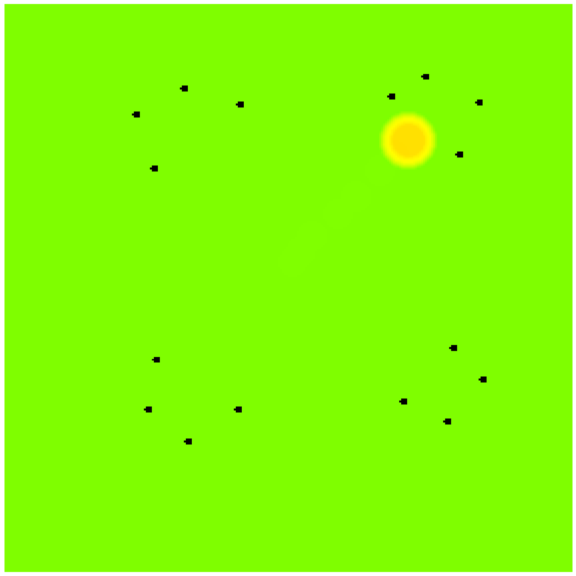


Figure 5.13. Leaving threshold testcase: Simulation 1: c = 0.0. Heat map view of the subject's positions during simulation

In the second simulation shown in Figure 5.14 and Figure 5.15, we set $c = 1.2$ which is equal to a mid-range value in initial interestingness scores of groups. This configuration causes the subject to visit more than one group and this is shown in Figure 5.14. Notice that when the subject joins a group, its distance to the center of that group is minimum and lower than all other groups. Thus, the lowest segment of every line in Figure 5.14 displays the time that the subject spends in the corresponding group. The heat map view in Figure 5.15 also shows traces of the subject switching groups in this simulation. This case shows a regular human behavior in a social setting: staying for some time with each group and then switching groups.

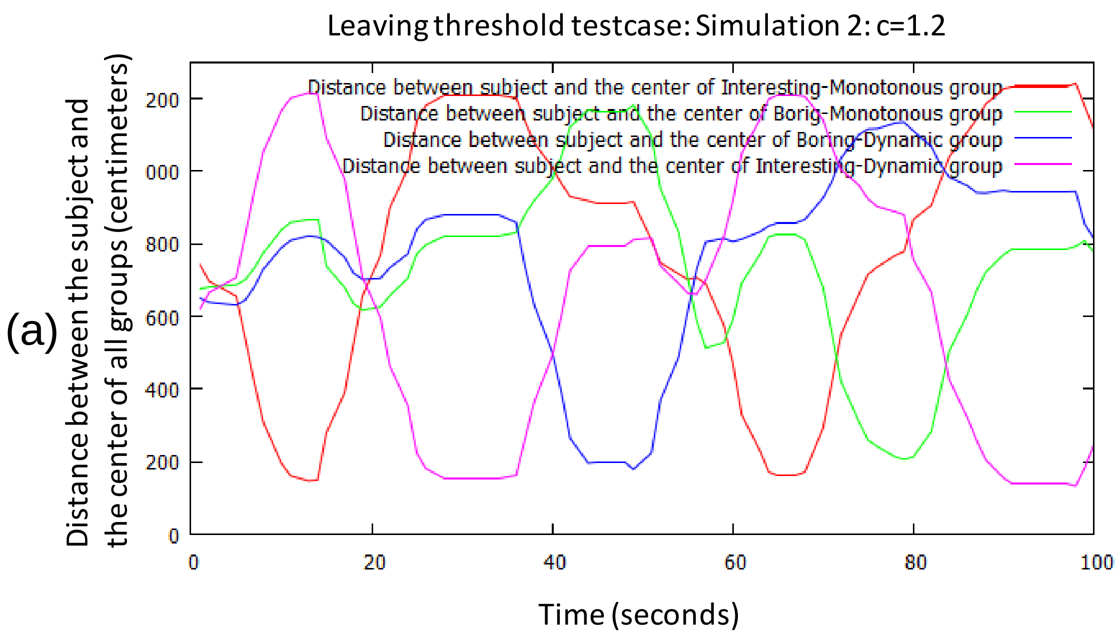


Figure 5.14. Leaving threshold testcase: Simulation 2: c = 1.2. Distance between subject and center of all groups plotted during simulation.

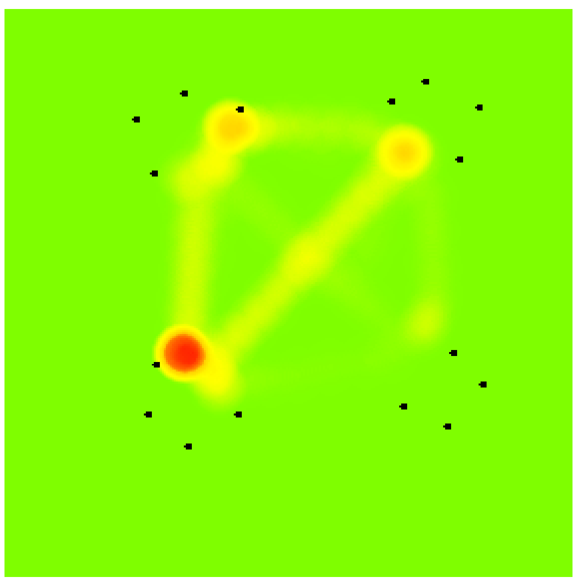


Figure 5.15. Leaving threshold testcase: Simulation 2: c = 1.2. Heat map view of the subject's positions during simulation

Finally, in the third simulation we set $c = 2.4$ which is the maximum value in the range of initial interestingness score of groups. As a result of this simulation, the subject leaves the groups faster; meaning that it spends less time in groups and more time moving from one group to another. This result is shown in Figure 5.16 and Figure 5.17. Comparing the heat map of Figure 5.15 to that of Figure 5.17 shows the heavier traffic between groups in the third simulation. Also, by comparing Figure 5.14 to Figure 5.16, one can see the lowest line segments are shorter in Figure 5.16, meaning that the subject has spent less time in each group in the third simulation.

A real-life case of a similar subject can be someone interested in interacting with a specific person in a social setting. Looking for that specific person, the subject switches groups very fast and spends little to no time in groups where the interesting person is not present.

(a)

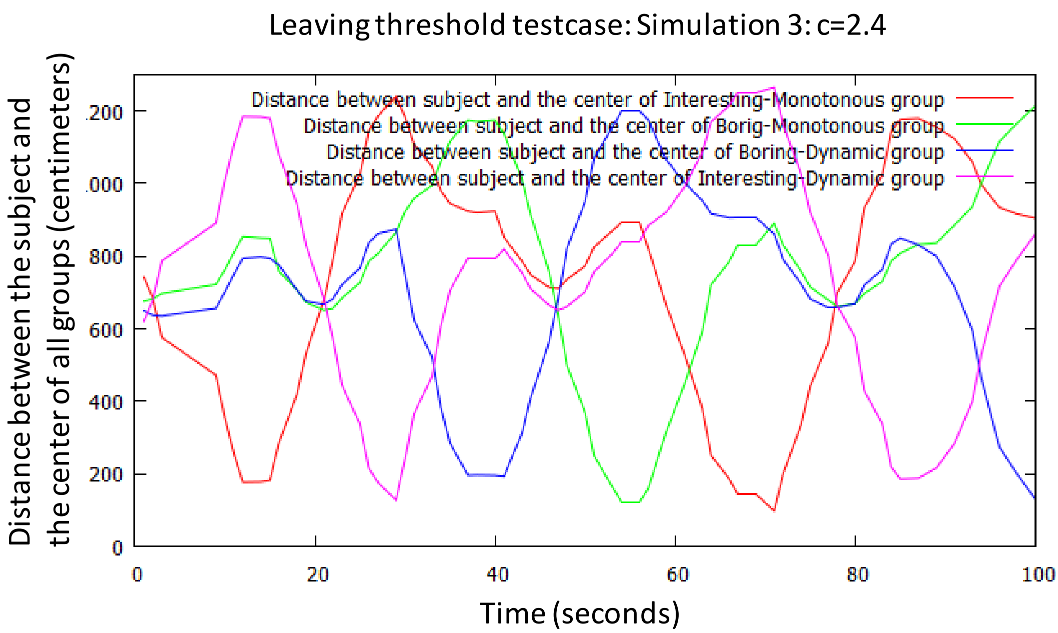


Figure 5.16. Leaving threshold testcase: Simulation 3: c = 2.4. Distance between subject and center of all groups plotted during simulation.

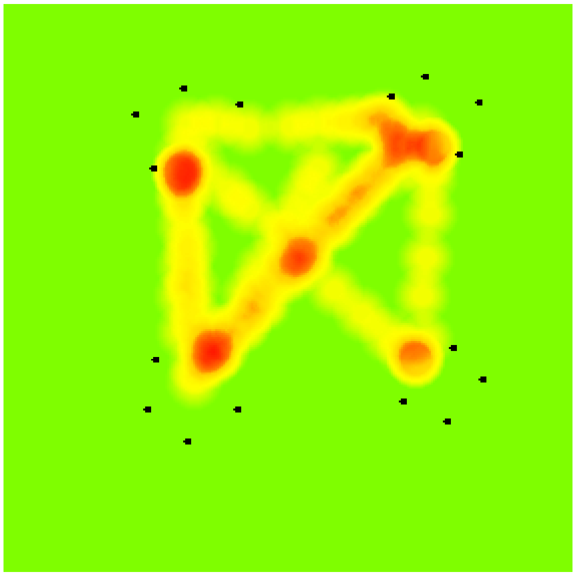


Figure 5.17. Leaving threshold testcase: Simulation 3: c = 2.4. Heat map view of the subject's positions during simulation

5.6. Summary

In this chapter we provided four testcases demonstrating the functionality of our social navigation system. The first two testcases are concerning the effectiveness of our social forces in navigating the subject to join a group and properly positioning it within the group. We demonstrated that the attraction force correctly navigates the subject to the circumference of the o-space of the target group while the repulsion force deviates and stops the subject in a distance from the group members so that its personal space does not get violated.

The third testcase show the effect of the interest model parameters on the pattern of the subject's trajectory. We demonstrated that by adjusting the rate at which the subject loses or recovers interest in dynamic or monotonous groups, we can control the pattern of its trajectory. The second simulation in this testcase confirmed that by setting slower decay and faster recovery rates for interestingness of dynamic groups, we can turn the uniform pattern of the trajectory to one with heavier traffic between the dynamic groups. Also this adjustment can be made in a way that the high frequency of having highly interesting dynamic groups prevents the monotonous groups from being visited at all.

Finally, in the fourth testcase we set a range of values for the personality factor of our leaving threshold to show how it influences the time our subject spends in each group. Simulation results for this testcase show that the subject with a lower personal threshold for leaving stays for a longer period in groups. In its most extreme case of the threshold 0 for leaving groups, the subject joins the group with highest interestingness score at the beginning and never leaves that group during the simulation.

Note that the testcase simulations in this chapter are provided as a proof of concept; we demonstrate that a subject more interested in dynamic groups visits them more often and a subject with no sensitivity to monotony of groups, like an autistic person, can stay in a group forever without getting bored. We believe these are examples of human-like behavior generated by our model. However, to prove that these behaviors are in fact human-like and our model exclusively generates human-like behavior, systematic evaluations are required. These systematic evaluations and studies are out of the scope of this thesis, as our main contribution is the development of the social navigation model as well as its implementation. Such studies are within the future works and will be presented by our research group in the future.

6. Conclusion

In this thesis we developed a social navigation model that generates human-like spatial behavior for a virtual human in a social setting with group dynamics. Our main scenario consists of a virtual environment with several groups of virtual characters, and a single character called the "subject" that exhibits social spatial behavior by joining and leaving groups and engaging in interactions with them.

There are similar spatial behavior generating models capable of navigating the subject toward and positioning it in the group, however, these models are limited to distance based group selection and they do not provide group-leaving behavior. In this work, we went beyond these models by contributing our group-leaving and group-revisiting mechanisms to the social navigation model. Due to this contribution, our model is capable of generating more human-like behavior in temporally large scale social scenarios. In an engineering approach, we employed behavior regulating mechanisms in humans to build a more realistic motivation for action selection and introduced a dynamic *interest* function representing our subject's interest in interacting with different groups. We use the interest function not only as the main factor for group selection in our model, but also as a mechanism for generating the group-leaving and group-revisiting behaviors. Hence our model is capable of generating a full cycle spatial behavior for a virtual human consisting of interest-based group selection, moving toward the group, positioning in the group, continuously evaluating group's interestingness and finally leaving the group to interact with another group.

Our ultimate goal in developing this model was to generate human-like social spatial behavior which matches the reference implementation provided by psychological literature. Thus, when the model is developed, the next step was to implement it and run several simulations of different social scenarios. We contributed our two-stage behavior generation implementation; in the first stage, our social spatial behavior planning algorithm plans the behavior using our social navigation model and in the second stage, the planned behavior is realized. The communication of the planned behavior is via BML commands between the two stages. We employed SmartBody software as our backend engine for animation and behavior realization tasks and implemented our social spatial behavior planning algorithm as a python module which is executed inside SmartBody's python engine. As a critical evaluation, it is worth mentioning that the architecture of the SmartBody platform does not allow external python modules such as ours to perform multithreading. This architecture limits the external modules to using its internal finite state machine for synchronization purposes.

The social spatial behavior planning algorithm is initialized using an XML file containing the initial scene data, as well as a configuration file that provides values for the parameters of the model. We simulated our model in several different social testcases and visually evaluated how human-like the behavior that our subject exhibited was. Also, in order to facilitate building and maintaining our testcases, we have designed and implemented an apparatus for visually creating the initial social setting. This testcase creating apparatus outputs an XML formatted file containing position, orientation and other information on group members and our subject, which is the input to our python module.

The social scenarios we simulated, covered a range of low to high initial interestingness and different monotony levels for groups, and demonstrated the effectiveness of our model in generating human-like social spatial behavior. All our visual results in the form of videos as well as our testcase creating apparatus and the source code is available to the reader through the iVizLab website for further studies (http://ivizlab.sfu.ca/research/SocialCharacterThesis/).

6.1. Summary of Main Contributions

Below is a detailed summary of our main contributions in this thesis, through which we built and implemented a social navigation model capable of generating human-like spatial behavior in temporally large scale social scenarios.

- We improved and further developed social forces from Pedica and Vilhjálmsson's model (2008), so that the generated social behavior is planned rather than reactive.
- We built a social navigation model that is capable of generating human-like social grouping behavior for non-player characters in stationary to semi-stationary social game scenes. Here, by semi-stationary scenes we refer to social scenes in which if group members are moving, they closely move with other group members so that the group is still detectable by an observer after the movement
- We went beyond group-joining and built group-leaving and group-revisiting behaviors into our social navigation model. Together, these three behaviors generated a full cycle of social spatial behavior for our subject character, which is closer to that of humans in temporally large scale social scenarios.
- We employed the concept of *interest* as the virtual character's motivation for action selection. This motivation is more realistic compared to distance-based group selection, in the sense that interest is a dynamic function. Because of its dynamism, interest can decrease over time and result in group-leaving behavior, whereas distance remains static as soon as the character joins a group.
- We provided a dynamic representation of interest based on the behavior regulating mechanisms of habituation and boredom in humans, using an engineering approach.
- We implemented our proposed social navigation model in a two-stage behavior generation process. In the first stage, our social spatial behavior planning component plans the behavior while in the second stage, the planned behavior is realized using the SmartBody software.
- We created a process for initializing our social navigation model with information about the initial scene, and implemented a testcase designer tool to facilitate design and effective maintenance of testcases.
- We simulated several social testcases using our system as proof of concept for our model.
- Finally, we offer public access to all our source codes and other resources through http://ivizlab.sfu.ca/research/SocialCharacterThesis/ for further testing and evaluations of our model.

6.2. Future Works

Our social navigation model and the behavior planning algorithm are the outcomes of the first steps in a larger project aimed at building a social and affective character framework. There are improvements from both modeling and implementation perspectives that can be performed on this work and the results should be systematically evaluated as well. In this section, we provide an outlook of the possible improvements within each scope.

Our main contribution of this thesis is the development of our social navigation model as well as the social spatial behavior planning algorithm that realizes it. The testcase simulations we presented in chapter 5 are proofs of concept and supposed to provide the reader with examples of the behaviors generated by our model, which we visually evaluated as human-like. To confirm that these generated behaviors are actually human-like, systematic quantitative and qualitative studies are required to be run on the model, with real humans observing and evaluating the subject's behavior in different settings. Model intrinsic testing can also be performed on our social navigation model to confirm its convergence and consistency of the behaviors generated in all testcases. These testing and evaluation processes are our main future work to be present by our research group.

From the model's point of view, our current social navigation model plans position, rotation and timing information for navigating the subject. However, spatial behavior can also be expressive behavior and be utilized for communicating affective information and social relationships (Inderbitzin, Valjamae, Calvo, Verschure & Bernardet, 2011). We believe an interesting augmentation to our model would be planning the expressive factors of spatial behavior. In particular, interestingness of the groups can be utilized as a source that influences the pace, style and manner of the subject's locomotion toward them.

Integration of the close-up behavior planning is also another possible improvement to our model. Here, by close-up behaviors we refer to the non-verbal behaviors that the subject uses while in a group, to communicate cues and intentions. Such behaviors include gaze, facial expressions and stance. Currently our subject does not exhibit any such behaviors to reflect its interest in a group while in the in_group state and that is not considered human-like. There are models available in the literature, which use interest and attention information to generate proper close up behaviors. One example of these models is presented by Peters et al. (2005) which generates interest based gaze behavior. Integration of similar models to our social navigation system can result in generation of more human-like behaviors.

On the other hand from the implementation perspective, an area of improvement is the real-time visualization of the interestingness score of groups. In our current implementation, the monotony score of groups is visualized using animation snippets that are executed on group members in real-time. But for the interestingness scores, we only provide initial value visualization through the appearance of members and no other real-time visualization is available for the interestingness of the groups. Having a visual presentation of this information is important because as an observer, one needs to be aware of the environmental information in order to fully comprehend the behavior of our subject. Our suggested solution for this problem is to create over-head bar charts for our groups similar to the one shown in Figure 6.1 from Defense of the Ancients (DotA) game[8]. These bar charts can be color coded and contain two or more bars, representing initial and real-time interestingness scores of each group.

Figure 6.1. Example of an over-head information bar chart used to display extra information for the game character (from DotA game). Adapted from http://www.starcraft-esp.com/foros/dota2-t9572-330.html

Finally, we are interested in decoupling our social spatial behavior planning algorithm from SmartBody and turning it to a standalone planning application that can communicate to other behavior realization platforms as well. Currently, because of high

[8] Official DotA website: http://www.playdota.com/

cohesion between our behavior planning module and SmartBody, there is no explicit line for the observer to differentiate between the planned behavior and its realization. For instance, a glitch observed in the subject's trajectory can either be caused by the behavior planning algorithm or the path planner component of the SmartBody and that makes it more difficult to evaluate the model independent of its realization. However, a standalone planning application can be utilized in combination with different behavior realization frameworks and by comparing the generated results, we can better evaluate the effectiveness of our social navigation model.

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Appendix A.

Supplementary Materials

All supplementary materials to this thesis are accessible online through the iVizLab website via http://ivizlab.sfu.ca/research/SocialCharacterThesis/. Below we provide a short description and usage guideline for each file.

Source Code

The SourceCode.zip file contains the Python scripts implementing our social navigation model explained in the thesis. To run this module you will need the SmartBody source code available for download at: http://smartbody.ict.usc.edu/download. After downloading the SmartBody's source code please follow the steps below:

- Unzip the contents of this zip file into \data\sbm-common\scripts
- Point to your testcase.xml file in the config.ini at \data\sbm-common\scripts\SocialCharacterProject
- Run sbm-fltk.exe from \bin\smartbody\sbm\bin
- Load run-simulation.py from \data\sbm-common\scripts\SocialCharacterProject

Testcase Designer Apparatus

The TestcaseTool.zip file contains the Testcase designer apparatus describes in section 4.5.3 of the thesis. To use this tool, download and unzip the contents of this file in your location of preference and then run TestCaseDesigner.exe. For more information on how to use this tool please refer to section 4.5.3 of the thesis.

Testcases

This folder contains additional resources for the testcases mentioned in chapter 5 of this thesis. Each inner folder represents a testcase mentioned in chapter5. For every simulation the reader can find the following files in the corresponding folder:

- The XML file used to create the initial scene
- The configuration file used for that simulation
- The video recording of the simulation
- A description.txt file describing what happens in the simulation

Also available for "Interest Model" and "Leaving threshold" testcases are:

- Log.dat: containing the subject character's distance to the center of all groups during simulation. Employed for creating plots of figures 41, 43 and 45 in the thesis
- heatmap.dat: containing the subject character's position information during simulation. Employed for creating the heatmaps of figures 36, 39, 42, 44 and 46 in the thesis.
- interestingness.dat: containing the interestingness scores of all groups during simulation. Employed for creating plots of figures 37 and 40 in the thesis.
- Subject's positions heatmap.bmp: the heatmap view of the subject character's positions during simulation.

Each testcase folder is describes separately below.

Attraction Force Testcase

The goal of this testcase is to demonstrate functionality of the attraction force for group-joining behavior in our social force field. In this simulation, subject starts moving from a point outside the group and walks toward the group till it completely joins the group. Here, subject's trajectory shows the path in which the attraction force navigates the subject. At the end of the video one can observe that subject's final direction is correctly set toward the center of the group and finally, the subject has ended up in a position that gives the whole group a roughly circular shape, providing direct, equal and exclusive access to conversation for all group members.

- Video file: Attraction force.avi
- Testcase xml file: AttractionTest.xml
- Configuration file: config.ini

Repulsion Force Testcase

In this testcase we show the functionality of our repulsion force for group-joining behavior in our social force field. In this simulation, subject starts moving from a point outside the group and walks toward the group till it completely joins the group. Unlike the attraction testcase, arrangement of the group members in this testcase does not allow for the subject to be positioned on the circumference of the o-space of the group without its personal space being violated. The reader can observe that from 3rd second forward in the video, not only the repulsion vector deviates the subject to the right to keep proper distance from the Doctor, but also causes the subject to stop earlier, so that its personal distance is not violated.

- Video file: Repulsion force.avi
- Testcase xml file: RepulsionTest.xml
- Configuration file: config.ini

Interest Model testcase

Our goal in this testcase is to demonstrate the effect of parameters of interest model on the subject's trajectory and visualize if the result is human-like. The initial scene of the testcase consists of four groups that are boring-dynamic, interesting-monotonous, interesting-dynamic and boring monotonous as shown in Figure 5.2 of the thesis. We use two different sets of configurations of interest model for our dynamic groups in this testcase and show the resulting trajectories. The testcase includes two simulations; in the first one, parameters of interest model are configured similarly for both dynamic and monotonous groups. In the second simulation though, we set a slower decay and faster recovery rate of interest for dynamic groups and visualize how this modification influences the pattern of the trajectory of the subject.

In simulation 1, using the trajectory view, one can observe that the subject has visited and interacted with all four groups in a roughly uniform pattern. In addition, the heat map view shows that the subject has spent the lowest amount of time with the boring-monotonous group. Finally, the path between the two interesting groups has been walked the most according to the heat map view.

In simulation 2 the pattern of movement is no longer uniform compared to simulation 1. Instead, the subject spends considerable amount of time going back and forth to visit dynamic groups on the left side of the scene. The interesting-monotonous group is also visited intermittently but on a lower frequency.

- Video file 1: Similar decays and recoveries.avi

- Video file 2: Slow decay faster recovery for dynamic groups.avi
- Testcase xml file: InterestModelTest.xml
- Configuration file: config.ini
- Subject's positions heatmap.bmp: Heatmap view of the subject's positions during simulation
- heatmap.dat: contains subject's position data during simulation. Used to create the heatmap view
- interestingness.dat: contains interestingness values of all groups during simulation. Used to draw interestingness plots
- Log.dat: contains distance between subject and center of all groups during simulation.

Leaving Threshold Testcase

In this testcase the effect of personality factor of subject (parameter c in equation 15) on the leaving threshold is demonstrated. The initial scene arrangement is the same scene as interest model and we ran three simulations for this testcase with c ranging from 0 to mid and maximum values; these values are set relative to the maximum initial interestingness of groups.

In simulation 1 we have c=0, meaning that the subject never gets bored of any task. One can observe that at the beginning of video the subject joins the interesting-monotonous group and never leaves it afterwards. In the second simulation we set c=1.2 which is equal to a mid range value in initial interestingness scores of groups. This configuration causes the subject to visit more than one group. In the third simulation we set c=2.4 which is the maximum value in the range of initial interestingness score of groups. As a result of this simulation the subject leaves the groups faster; meaning that it spends less time in groups and more time moving from one group to another.

- Video file 1: zero c.avi
- Video file 2: medium c.avi
- Video file 3: max c.avi
- Testcase xml file: InterestModelTest.xml
- Configuration file: config.ini
- Subject's positions heatmap.bmp: Heatmap view of the subject's positions during simulation
- heatmap.dat: contains subject's position data during simulation. Used to create the heatmap view
- interestingness.dat: contains interestingness values of all groups during simulation. Used to draw interestingness plots
- Log.dat: contains distance between subject and center of all groups during simulation. Used to plot distances.