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SPECIAL ISSUE PAPER

A model for social spatial behavior in virtual characters

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ABSTRACT

Plausible spatial behavior is a key capability that autonomous virtual characters need in order to provide ecologically valid social interactions. However, there is a lack of psychological data on spatial behavior in the larger scale social settings and over extended periods of time. In this paper, we present a social navigation model that aims at generating human-like spatial behavior for a virtual human in a social setting with group dynamics. We employ an engineering approach by defining a dynamic representation of interest and then using it as the psychometric function that regulates the behavior of the agent. We evaluate our model by means of two test cases that address different aspect of the model and serve as a proof of concept. Our work is a step toward models for generating more plausible social spatial behavior for virtual characters that is based on both internal dynamics and attributes of the social environment. Copyright © 2014 John Wiley & Sons, Ltd.

KEYWORDS

social navigation; group dynamics; virtual characters; behavior regulation

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1. INTRODUCTION

Autonomous anthropomorphic virtual characters are an integral part of ecologically valid social interactions in many computer games and in virtual reality-based applications for training, education, care giving and so on. A considerable research effort is undertaken to model virtual humans 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 vision 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 nonverbal communication, having internal models for desires and intentions and exhibiting affective qualities such as emotions. 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*. Not only social spatial behavior provides access to the environment and clusters of other individuals near the virtual character, but it is also a way of nonverbally communicating desires and intentions through whole-body movements.

1.1. Related Work

A significant 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 [1] is one of the most prominent theories. Hall's "proxemics" theory [2] is another psychological theory that suggests a spatial structure in interactions between two participants. According to Hall, 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. Hall's theory has been substantiated in numerous studies, both in the real world (e.g., [3]) and in virtual environments [4–6]. A second key theoretical framework related to social spatial behavior is Kendon's F-formation theory [7] that strives to conceptualize the spatial arrangement of group members in a conversational group. Kendon defines a *transactional space* in front of every individual that they direct their attention to. Consequently, in a conversational group, members arrange themselves so that their transactional spaces overlap and a joint transactional space ("o-space") is created. This arrangement—referred to as F-formation—allows for direct, equal and exclusive access to the conversation to all members.

A large number of approaches and models address the issue of spatial behavior and group dynamics. The existing models can be broadly categorized as particle or agent based, with the latter used preferentially for modeling detailed group dynamics. In particle based, models plan a specific type of movement for the crowd and then realize it by applying forces on all particles. Conversely, in an agent-based approach, the number of individuals is relatively small, and each individual is equipped with a local control model of simple to complex behaviors. In his seminal work, Reynolds [8] simulated the aggregate motion of a flock of birds using a distributed agent-based approach. In his work, each bird is navigated according to its local perception of the environment as well as the rules of physics applicable to its motion. Musse and Thalmann [9] simulated crowd behavior in real time using a hierarchical structure to describe the crowd members. In a smaller scale scenario, Rehm *et al*. [10] focused on social rules of interpersonal interaction and built a model of social group dynamics inspired by theories from social sciences that draws from proxemics theory 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. In another dyadic conversation scenario, Sun *et al*. [11] employed parameterized behavior trees to coordinate interactions of conversation parties (agents) where the attributes and states of the agents determine the flow of the behavior trees. In similar approaches, Rist and Schmitt [12] employed simple liking relationships to emulate group dynamics in a person-to-person negotiation scenario. Thórisson *et al*. [13] proposed a turn-based architecture to model a multiparty dialog scenario in which a set of perceptions activate a subset of eight dialog contexts and action modules, with time being the main driver of this process. Jan and Traum provided 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 [2] as well as the F-formation theory [7]. 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.* [10] but more complete in the sense of considering a multiparty conversation. One of the most promising approaches is the social navigation model by Pedica and Vilhjálmsson [14] that covers generating both positional and orientational information, for navigating the character. The model builds on a social force field model for navigating 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.

1.2. Spatial Behavior Based on Dynamic Social Motivation

In this paper, we present a social navigation solution capable of generating social spatial behavior for human-like virtual characters in a temporally large-scale social scenario. We build our model based on the model proposed by Pedica and Vilhjálmsson [14] and further develop it to be able to effectively generate human-like social spatial behavior using an internal dynamic representation of social motivations for group selection and group leaving. We benefit from the psychological notions of "boredom" and "habituation" that act as behavior regulators influencing the social motivation in this process. Here, by habituation, we refer to the process through which a subject's response to a stimulus decreases as a result of being repeatedly exposed to it. The dynamic change in the motivational value leads to group-leaving and group-revisiting mechanisms in our social navigation model. Lastly, 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 character animation system [15]. This implementation is used to simulate sample test case scenarios that serve as a proof of concept for our model.

2. METHODS

The social situation we model comprises one or more groups of characters and an individual virtual character—the subject—that regulates its behavior with respect to the groups. Groups are formed by three or more virtual characters that have the attributes position, spatial orientation and "activity" level. Additionally, the subject character attributes an initial "interestingness" value to each group member, indicating how desirable interaction with the character is. The source of the interestingness value can be the member's personal or social attributes such as gender or social status. Next to the individual values, we calculate per-group values for interestingness and activity.

2.1. Social Spatial Behavior Regulation Model

Our model generates a full cycle of social spatial behavior that starts with selecting the most interesting group for the subject character to join. Subsequently, the subject moves toward the selected group and positions himself/herself within that group. While "interacting" with group members, the subject constantly evaluates the group's interestingness in order to determine when to leave the current group for another one. Broadly speaking, our model comprises two states: "out_group" and "in_group" (Figure 1). In the out_group state, our model is in continuous search for subject's next target group to join. Selection of the target group is based on real-time

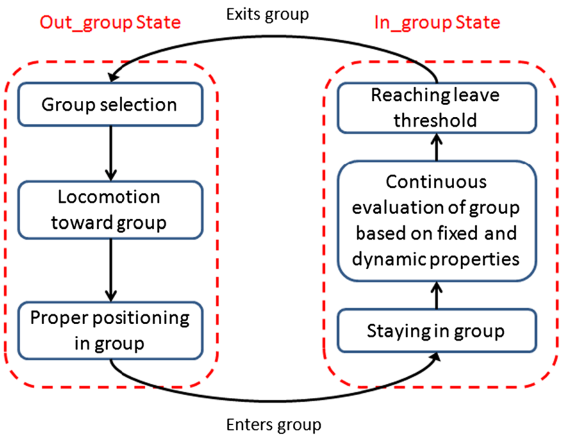


Figure 1. State–space view of the behavioral cycle underlying the action selection in our model.

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 latest target group, the transition from out_group state to in_group state completes. In the in_group state, the real-time evaluation of the interestingness value and monotony scores continues in search for a leaving (boredom) threshold. Reaching this threshold causes the subject character to leave the group to make the transition from in_group state back to out_group state.

2.1.1. The Improved Social Force Field.

Pedica and Vilhjálmsson [14] modeled spatial behavior of a single character in group dynamics within a shared virtual environment using a force field of three distance-based forces of cohesion, repulsion and equality. We adapted this social force field model and improved it to form our two social forces of attraction and repulsion.

There are two main parameters to the *attraction force*: the center of the group and the proper conversational distance between the subject and the center of the group when the subject joins the group. Assuming a roughly circular formation for groups, equation (1) shows the calculation of the group center c with N_g being the number of the group members and r_i being the vector representing the position of the i^{th} group member.

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

Also, based on Kendon's F-formation theory [7], the proper position for the subject to join a group is the circumference of the o-space of that conversational group. We consider 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 (2).

$$d_{\text{avg}} = \frac{1}{N_g}\left(\sum\nolimits_i^{N_g} r_i - c\right) \tag{2}$$

Utilizing the previously mentioned definitions for c and d_{avg}, we defined our attraction force in equation (3), which factors the cohesion and equality forces in the basic model. The 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.

$$F_{\text{attraction}} = \alpha\left(\|c - r\| - d_{\text{avg}}\right)\frac{c - r}{\|c - r\|} \tag{3}$$

In contrast to the reactive *repulsion force* used in [14], we use a predictive repulsion force that is activated before the actual violation of the personal distance. This prevents the subject character from moving farther ahead when the group configuration results in an undesirable situation. The predictive mechanism in our repulsion force is achieved by substituting the personal space with social space [2] of the virtual character within the original repulsion force. 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. Equation (4) shows the modified R with N_s being the number of group members within the social area of the subject character.

$$R = \sum\nolimits_i^{N_s} (r_i - r) \tag{4}$$

Our implementation of the repulsion force in the [14] model demonstrated that the magnitude of the force requires adjustment as it sends the agent far back from the group; thus, our final improvement was to reduce the magnitude of the repulsion force. Equations (4) and (5) define our improved version of the repulsion force.

$$F_{\text{repulsion}} = -\left|\Delta_p - d_{\text{min}}\right|\frac{R}{\|R\|} \tag{5}$$

Similar to the original repulsion force, our improved version can result in movement in the wrong direction if the subject character is positioned inside the o-space of a group at any point in time. But with the assumption of starting at time 0 in the out_group state, we can always avoid this situation as the early activation of the modified repulsion force always prevents the subject character from entering o-space of groups.

2.1.2. From Physical to Psychological Distance.

To account for the subjectivity of the experience of distance [16], we included a non-linear mapping from physical to "psychological" distance, which is a plausible hypothesis formalized based on the "Zurich model of social motivation" [17]. Hence, 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.

The mapping from physical to psychological distance (D_{psy}) is given in equation (6).

$$D_{psy}\left(D_{phy}, D_{max}, s\right) = \begin{cases} \dfrac{D_{max}.D_{phy}}{s.\left(D_{max} - D_{phy}\right) + D_{max}.D_{phy}} & \text{for } D_{phy} < D_{max} \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

Parameter D_{max} is the maximum physical distance perceivable by our subject character, D_{phy} is the actual physical distance between the subject character and the group or a group member, and s is a control parameter determining the rate at which psychological distance grows with physical distance. Both D_{max} and s are parameters of our model that not only normalize all distances to a value within [0, 1] interval but also make the model independent of the size of the virtual environment.

2.2. Interest-based Social Spatial Navigation

The core assumption in our model is that an important component of the motivation for engaging in interactions is novelty seeking, internally represented as "interest." We conceptualize interest as a dynamic function of time that provides the "leave-group" mechanism in our model. Formally, the interestingness of group g is a function of time (t) and level of activities (monotony score) of the group (Δ_g). If the subject is in the out_group state, our model continuously evaluates the interestingness scores of all groups and selects the group with the highest perceivable value as the target group. By perceivable interestingness score ($\text{Interestingness}_g(t, \Delta_g)$), we mean the interestingness score of the group scaled to the psychological distance at which the subject perceives that group. Our ultimate attraction force that derives this process is shown in equation (7).

$$F_{attraction} = \alpha\Big(\text{Interestingness}_g\left(t, \Delta_g\right)\Big).\big(D_{psy}(\|c - r\| - d_{avg}, D_{max}, r)\big)\frac{c - r}{\|c - r\|} \quad (7)$$

After the subject joins a group, our model continuously re-evaluates the interestingness score of the current group and monitors this score. If it drops to the leaving threshold, the subject will leave the group.

2.2.1. Interest Model and Calculation of Interestingness Score.

Drawing from previous work on habituation [18] and boredom [19,20], we modeled interest in our solution using a decreasing function of time, which is shown in equation (8). Initially, 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 starts to dynamically change as a function of time, which is in compliance with the habituation theory. Hence, at time 0 of joining a group, the interestingness score of that group 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, the interestingness score of the group decreases proportional to its monotony score.

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, the more alternative stimuli our subject can find in interacting with the group, and thus, it remains in the group longer. In long term, the subject will eventually experience boredom in its current group, which is influenced by personality factors of the subject as well as interestingness and monotony scores of other groups in the environment. The subject character then leaves the group in order to find alternative stimuli in interacting with other groups in the virtual environment. We employ the personality factors of the subject as a buffer that can help fine-tune the interest model and reduce its predictability.

Higher monotony scores translate to faster decay. This monotony score is then used as a control parameter in our model of interest. In equation (8), 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.

In our model, we accommodate for inter-individual differences by incorporating a parameter that represents the minimum interestingness score at which the subject leaves a group. We refer to this parameter as "boredom threshold" and denote the threshold for group g by I_{min_g}.

As we assume that humans are likely to interact with a conversational group more than once in a social setting, we include recovery of interest 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. In equation (8), 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. To prevent the subject from returning to the same group to soon after leaving it, we include a mechanism for "inhibition of return" [21] in our model. We achieve this by pulling the interestingness score of that group to 0 the moment the boredom threshold is reached. We included this shunting effect in equation (8) by setting the first time condition to $t < t_0 < T_{\max_B}$, assuming that $t_0 < T_{\max_B}$ is the time of reaching the leaving threshold. In Figure 2, we summarize the interest mechanism used in our model.

when to generate the BML locomotion command to make the subject character leave the group for another. The leaving threshold is calculated using a combination of the subject's characteristics and the interestingness scores of other groups (equation (9)).

$$I(t, T_{\max_B}, m_B, t_0, T_{\max_R}, m_R) = \begin{cases} \dfrac{m_B.(T_{\max_B} - t)}{m_B.(T_{\max_B} - t) + T_{\max_B}.t} & \text{for } t < t_0 < T_{\max_B} \\ 0 & \text{for } t = t_0 \\ \dfrac{T_{\max_R}.t}{m_R.(T_{\max_R} - t) + T_{\max_R}.t} & \text{for } t_0 < t < T_{\max_R} \end{cases} \quad (8)$$

2.3. Implementation

We delegate the tasks of animation, rendering and behavior realization to the SmartBody platform [15] and develop our own social spatial behavior planning engine as a Python module to plan the social spatial behaviors. Our behavior planning engine generates behavior markup language (BML) commands that SmartBody realizes. Initialized by the initial scene information as well as the interestingness scores of the members, our engine continuously calculates and updates the interestingness of groups. This updated score is then used for group selection and calculation of boredom threshold. Group selection is the process in which our engine continuously calculates the attraction and repulsion forces toward each group in the environment and selects the group with maximum value. Our engine makes use of the position information of the selected group based on interestingness score to generate commands that navigate the subject character to join a group while in out_group state. In the in_group state, the updated interestingness score of the current group is compared with the leaving threshold to determine

$$I_{\min_{target}} = C + \frac{\beta}{n-1} \sum_{g \neq target} I_g(t, T_{\max_B}, m_B, t_0, T_{\max_R}, m_R) \quad (9)$$

In equation (9), C is a constant value that 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.

3. RESULTS

We evaluate our work by means of two test cases that address different aspect of our social spatial model and serve as a proof of concept and illustration of the model's capability to generate a range of dynamic behaviors.

3.1. Test Case "Interest Model"

With this test case, we demonstrate the effect of parameters of the interest simulation part of the model on the subject's

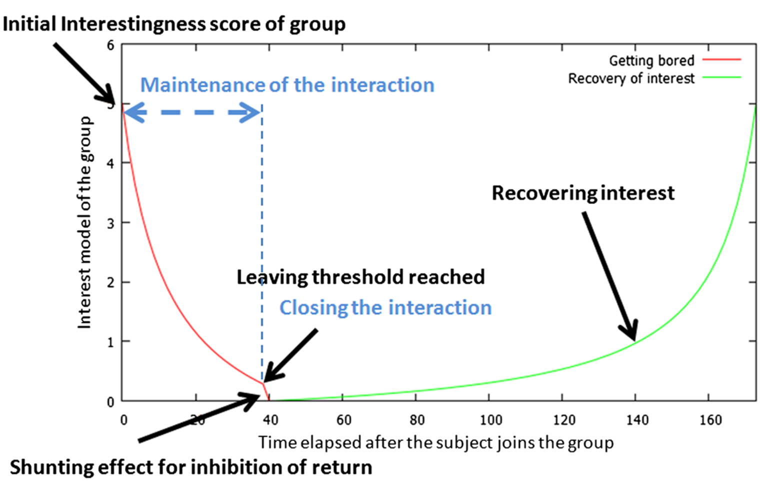


Figure 2. Summary of the dynamics of "interest."

spatial behavior. The initial scene of the test case consists of four groups on high and low ends of two axes of "dynamism" and "interestingness." The groups are labeled

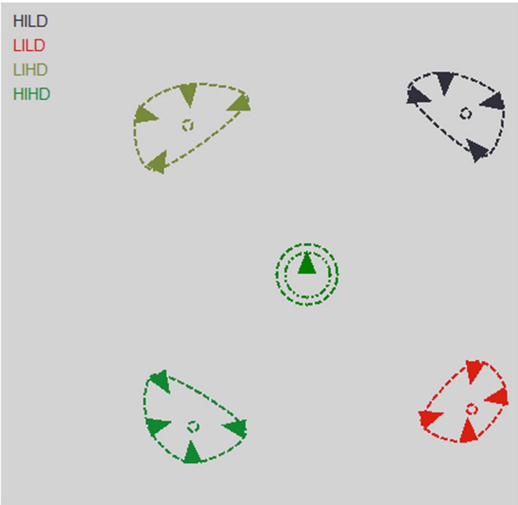


Figure 3. Initial spatial arrangement of groups and members for the "interest model" test case.

"low interestingness high dynamism" (LIHD), "high interestingness high dynamism" (HIHD), "low interestingness low dynamism" (LILD) and "high interestingness low dynamism" (HILD) (Figure 3). In this test case, we change the parameter configuration of the interest model for our groups of high dynamism within two simulations; in the first simulation, which we use as our reference, the same interest model configuration is used for all groups, while in the second simulation, we use slower decay and faster recovery parameters for the groups of high dynamism.

3.1.1. Simulation 1: Equal Interest Model Across Groups.

Figure 4 shows the graph of interestingness given the configuration used in the first simulation. For all groups on both ends of the dynamism axis, regardless of their interestingness, we set $T_{\max_B} = 10$, $m_B = 20$, $T_{\max_R} = 150$ and $m_R = 320$ in equation (8). Figure 5 shows the time course of the "interestingness scores" of all four groups in this simulation. Each "peak" corresponds to the event of the subject joining the corresponding group. We can observe that after 300 seconds, the subject has visited and interacted with all four groups in a roughly uniform pattern (Figure 6a). The heat map view (Figure 6b) shows that on the one hand, the

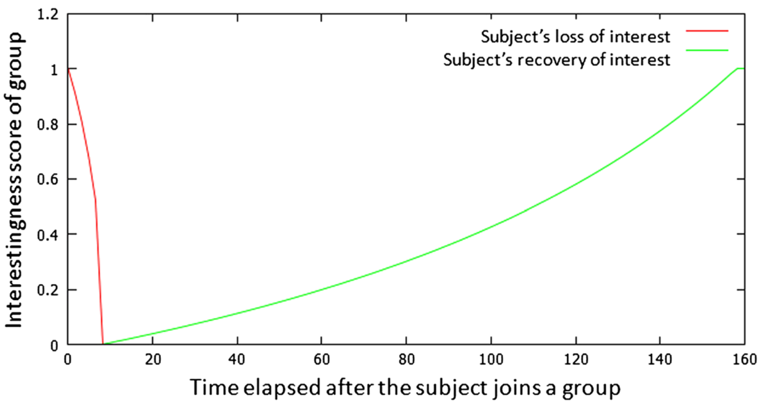


Figure 4. "Interest model" test case: simulation 1: the corresponding interestingness graph to similar interest model parameter configuration for all groups.

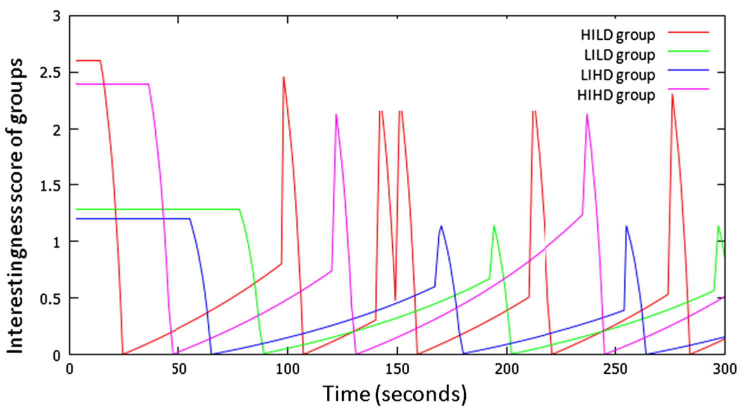
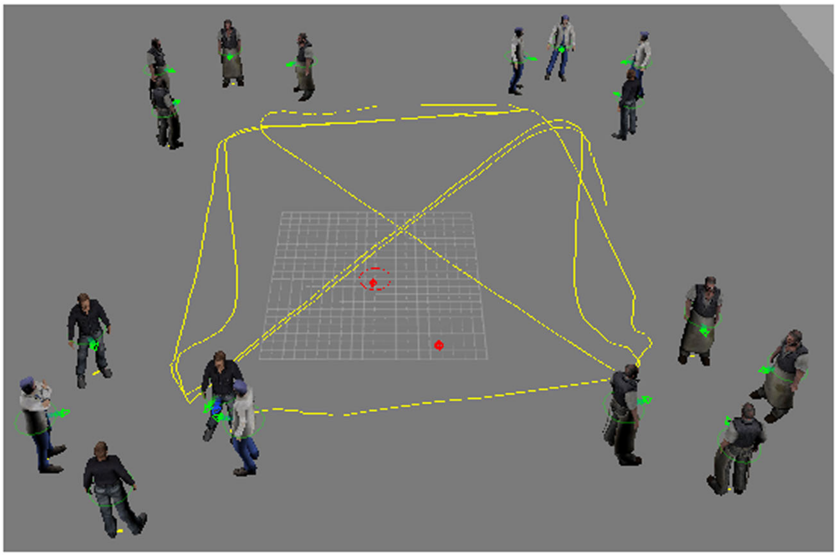
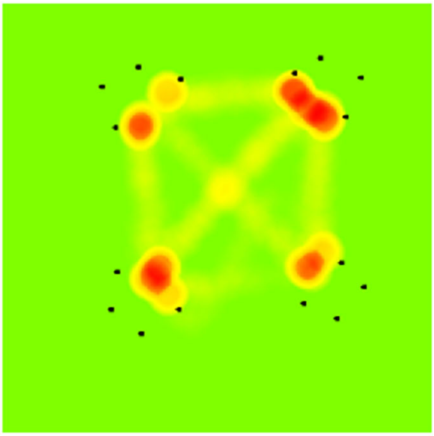


Figure 5. First simulation of the "interest model" test case: interestingness scores of all four groups plotted during simulation.



(a)



(b)

Figure 6. First simulation of the "interest model" test case: (a) pattern of trajectory of subject after 300 seconds. Graphical representation rendered using the SmartBody character animation system [15]. (b) Heat map view of the subject's positions.

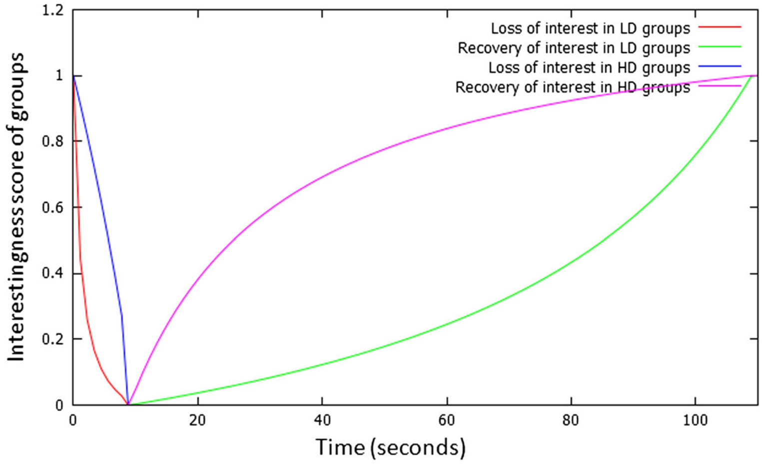


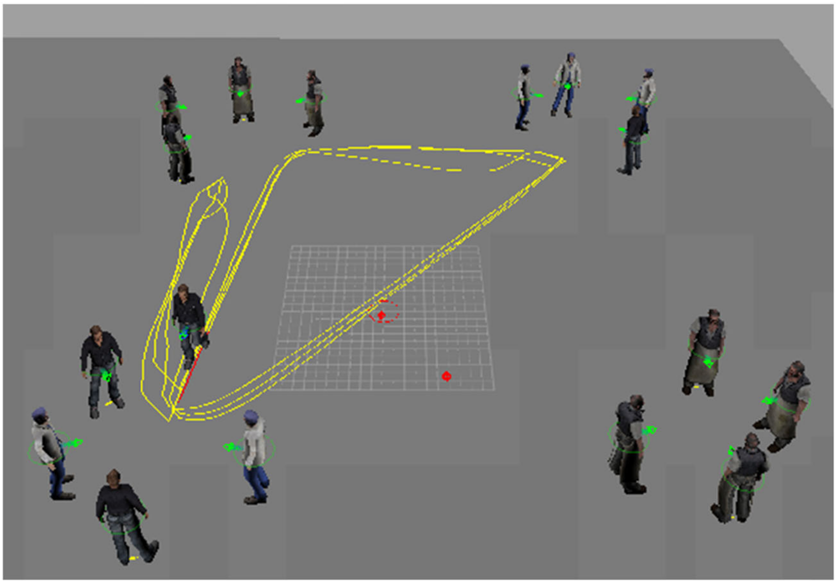
Figure 7. "Interest model test case" second simulation: slower decay and faster recovery for dynamic groups.

subject has spent the smallest amount of time with the LILD group and, on the other hand, the path between the two interesting groups has been taken the most frequently.

3.1.2. Simulation 2: Favoring Groups with High Dynamism.

In the second simulation, we change the configuration for our groups of high dynamism to $m_B = 13$ and $m_R = 20$, which results in slower decay and faster recovery. This configuration is illustrated in Figure 7. As a result of this configuration, the subject's trajectory changes quite markedly: The pattern of movement is no longer uniform, but instead, the subject spends a considerable amount of time going back and forth between the highly dynamic groups on the left side of the scene (Figure 8). The HILD group is visited intermittently with a lower frequency.

Both groups of low dynamism on the right side of the scene use the same parameters of the interest model, but having a high initial interestingness score, the HILD group is visited a few times during simulation, while the LILD group is left isolated. The interestingness plot of Figure 9 shows the reason why the LILD group is never visited by the subject: Because of the fast rate of recovery for dynamic groups throughout the simulation, there is always a group with higher interestingness score than the LILD group. Hence, a LILD fails to attract the subject. Conversely, the HILD group gains the interest back in a slow rate but at a higher value than the highly dynamic groups. It is for this reason that the subject visits HILD group approximately every 50 seconds.



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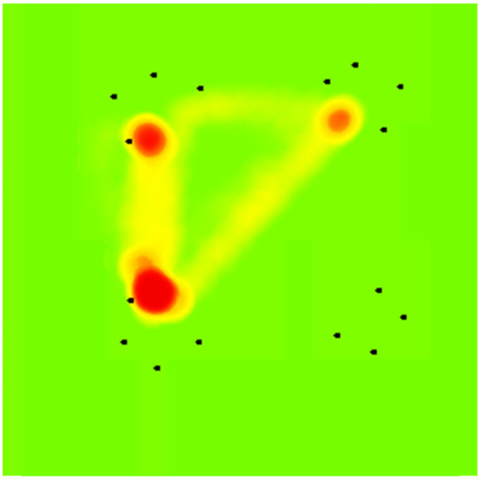


(b)

Figure 8. "Interest model" test case: simulation 2: (a) pattern of trajectory of subject at the end of running simulation; (b) heat map view of the subject's positions during simulation.

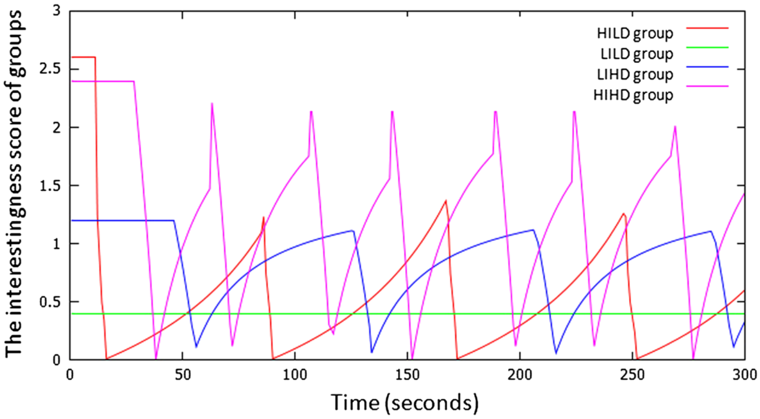
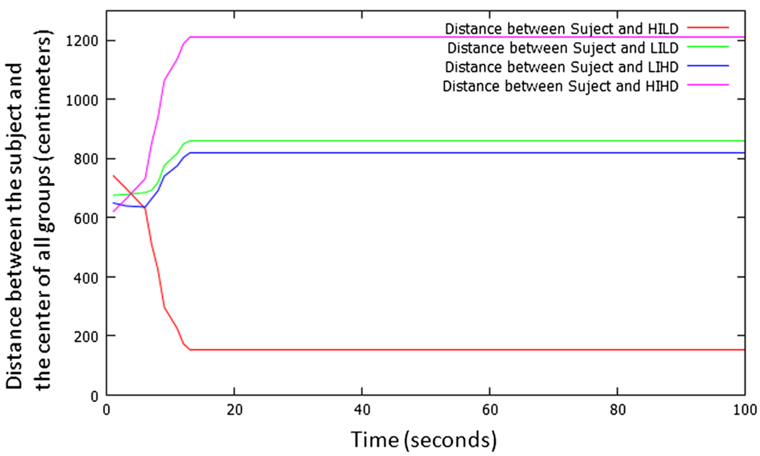
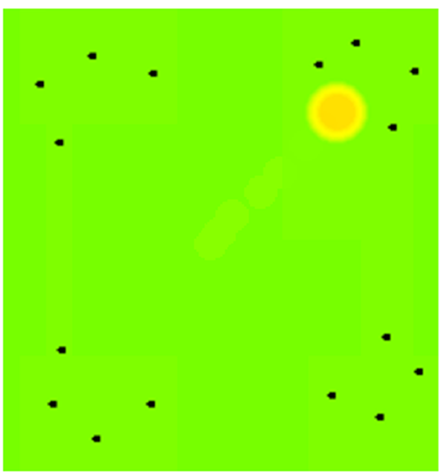


Figure 9. Interest model test case, second simulation: interestingness scores of all four groups. Observe slower decay and faster recovery of interest for highly dynamic groups.



(a)



(b)

Figure 10. Leaving threshold test case: first simulation ($C = 0\%$). (a) Distance between subject and center of each group during simulation. (b) Heat map of the subject's positions during simulation shows that the subject never switches groups.

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3.2. Test Case "Leaving Threshold"

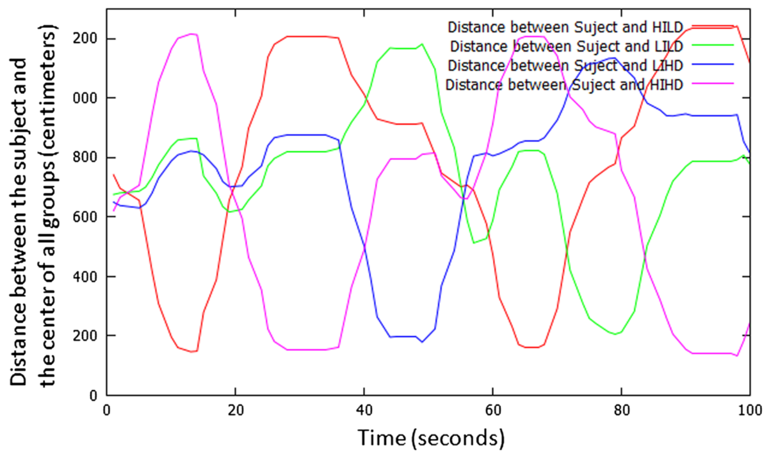
In this test case, the effect of the "leaving threshold constant" of the subject (parameter C in equation (9)) on the leaving threshold is demonstrated. The initial scene arrangement is the same as shown in Figure 3, and we ran three simulations for this test case with C ranging from 0% to 50% and 100% relative to the maximum initial interestingness of the groups with $\beta = 0$.

In the *first simulation*, we have $C = 0.0$ reflecting a subject that never gets bored of the groups (Figure 10). During the simulation, the lowest line in the distances plot (Figure 10a) corresponds to the group that the subject has joined, and we can see that there is no more than one such group in this simulation. The subject joins the HILD group at the beginning and never leaves that group. We consider never becoming bored of an activity or group a plausible variation of human behavior.

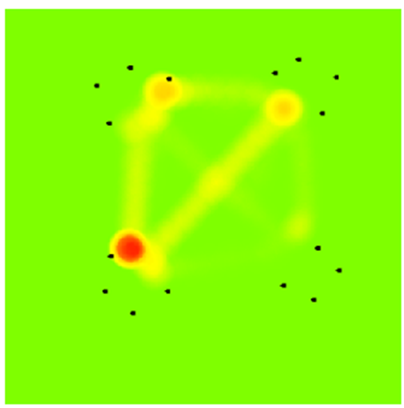
In the *second simulation*, we set $C = 50\,\%$ of the maximum initial interestingness of groups (Figure 11). This configuration causes the subject to visit all groups (Figure 11a).

This case shows a fairly plausible human behavior in a social setting: staying for some time with each group and then switching to another group.

Finally, in the *third simulation*, we set $C = 100\,\%$ of the maximum initial interestingness 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 (Figure 12). Compared with the previous simulation with $C = 50\,\%$ (Figure 11b), we can see a clear increase in transitions between groups (Figure 12b). An inspection of the time course of the distance between subject and center of each group (Figure 12a) shows that the lowest line segments are shorter compared with the previous simulation (Figure 11a), indicating that the subject has spent less time in each group in the third simulation. The behavior we observe in our simulation resembles a person interested in interacting with a specific person they are looking for; that is, the subject switches groups very fast and spends

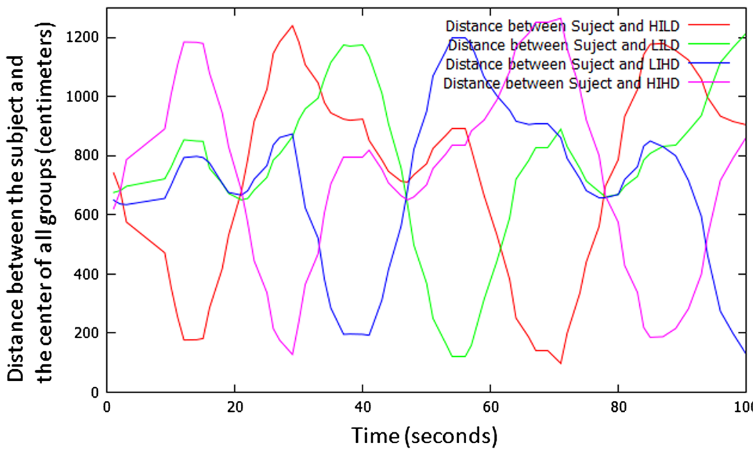


(a)

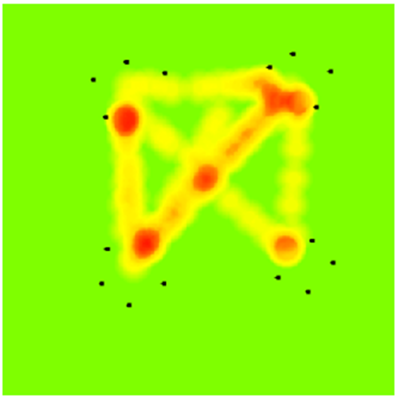


(b)

Figure 11. Second simulation of the "leaving threshold" test case ($C = 50\%$). (a) Time course of distance between subject and center of each group. The lowest segment of every line indicates the time that the subject spends in the corresponding group. (b) Heat map of the subject's positions.



(a)



(b)

Figure 12. "Leaving threshold" test case third simulation ($C = 100\%$). (a) Distance between subject and center of all groups plotted during simulation. (b) Heat map of the subject's positions during simulation.

little to no time in groups where there is no interesting person present.

4. DISCUSSION AND CONCLUSION

In this paper, we presented a social navigation model that aims at generating human-like spatial behavior for a virtual human in a social setting with group dynamics. Existing models are capable of navigating the subject toward and positioning it in the group but are limited to distance-based group selection and typically do not provide group-leaving behavior. We developed group-leaving and group-revisiting mechanisms, which we believe resulted in our model being capable of generating more human-like behavior in temporally large-scale social scenarios. 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. This interest function is our model's main factor for group selection as well as a mechanism for generating the group-leaving and group-revisiting behaviors. Hence, our model is capable of generating a full cycle of 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. We show the results from two test case simulations that demonstrate the functionality of our social navigation system. The test case "interest model" shows that by adjusting the rate at which the subject loses or recovers interest in groups of high or low dynamism, we can control the pattern of its trajectory and change it from a uniform pattern to one with heavier traffic between any subsets of groups, or prevent a subset of groups from being visited at all. Simulation results for the test case "leaving threshold" show that the subject with a lower leaving threshold constant 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.

We envisage two routes for further testing the model: Model intrinsic testing will assess the stability, convergence and consistency of the behaviors generated in a larger variety of test cases, while empirical studies with human participants who are observing and evaluating the virtual character's behavior will assess the plausibility of the social behavior generated by the model. In future version of the system, we plan to integrate close-up behaviors for gaze, facial expression and stance, as well as expressive qualities such as style and manner of movement [22]. Last but not least, we plan to employ the same model on all characters in the environment and study the emerging collective behavior.

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