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SPECIAL ISSUE PAPER

Simulating and animating social dynamics: embedding small pedestrian groups in crowds

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ABSTRACT

We present a crowd model informed by common ground theory to accommodate high-level socially aware behavioral realism of characters in crowd simulations. In our approach, group members maintain group cohesiveness by communicating and adapting their behaviors to each other. The resulting character behaviors in animations form a consequential chain interpreted as a coherent story by observers. We demonstrate that our model produces more believable animations from the viewpoint of human observers through a series of user studies. Copyright © 2013 John Wiley & Sons, Ltd.

KEYWORDS
group modeling; crowd simulation; common ground theory

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1. INTRODUCTION

Incorporating the sense of social intelligence for virtual characters is important to achieve plausible aggregate behavior in crowd simulations. Crowds are typically made up of multiple social groups [1,2] and generating believable group behaviors within a crowd has been a focus of many researchers in recent years [3–6].

A group is a social unit comprising several members who stand in status and relationships with one another. Behaviors of individual members are regulated in matters of consequence to the group. In group activities, people perform actions such as body movements, gestures, and eye gazes as means of participating with others in the group, whereas crowd simulation applications that consider group organization typically focus on overall formations and inter-member distances; Park *et al*. showed that communicative behavior within individual groups can impact the distribution of the simulated crowd as a whole [7,8]. Applying Herbert Clark's common ground (CG) theory [9] to model group behaviors in simulation, they demonstrated the impact of incorporation of their model on the dynamic congestion distribution in simulations but did not show that the model produced more correct or believable simulations.

We extend the group communicative behavior model because of Park *et al*. to accommodate high-level socially aware behavioral realism of characters in a crowd simulation. In narrative psychology, Bruner proposed an idea that humans make sense of intentional behaviors by taking them into narrative structures [10]. We employ this concept to test our CG-based crowd simulation (CGCS) model by determining whether the model yields purposive interpretations of the resulting animation. Through a series of perceptual user evaluation studies, we demonstrated that the believability of an animation is affected by communicative and social interactions among characters.

The remainder of this paper is organized as follows. In the next section, we discuss related works and Clark's CG theory. Then, we provide the design of our multi-agent system. Following this, we describe the CGCS model. The subsequent section presents the design of our user studies and the results. Finally, we draw conclusions and provide possible future research directions.

2. RELATED WORK

There have been extensive research on simulating crowd behaviors, and we refer the readers to the surveys [11,12]. We review some of the most relevant work to the group modeling and Clark's CG theory in this section.

2.1. Groups within Crowds

The incorporation of small group dynamics into a crowd model has been the focus of recent research interest. In some studies, walking patterns and spatial organizations of small groups are analyzed from collected video recordings [3,13,14]. The observed formations are represented as reference templates in a local coordinate system of a group and used to guide each group member's relative position [3]. Numerical models to include such formation influences are proposed in [13–15]. Maintaining the desired formations while walking is formulated as a collective optimization problem for group members in [4]. However, walking in a group is not just a matter of how to maneuver to reach a desired position at a low level. People communicate with other members and trade off certain action, path, and location according to the particular situation of a group. It is hard to mechanistically construct such higher-level behavioral activity completely from bottom up.

Data-driven (motion capture) methods of simulating various interactive motion patterns in groups are presented in [16,17]. However, these approaches are expensive techniques because of the computational complexity to create connecting transitions between data segments and also suffer from the lack of flexibility.

A behavioral aspect in group dynamics is also considered. The effect of actions and gestures, such as interacting distance, orientation, and synchrony of visual and aural cues of actions on the plausibility of conversing groups have been identified and applied to the simulation of groups of conversing characters in [5,6]. However, in these approaches, the selection of stance, movement, and motion is not tightly coupled to the underlying simulation model, and the sequence of character gestures does not draw a socially meaningful story. In our work, all character actions form a consequential chain so that results in a coherent story. Also, their approaches focus on generating static conversing characters, thereby limiting applications. Our model can handle sub-goals that may be generated stochastically or through interaction between agents and the environment and brings a variety of group interaction and movement patterns into simulations.

2.2. Common Ground Theory

People engage in a joint activity when they act in coordination with others to pursue a common goal. Clark's CG model views execution of a joint activity as a continuous negotiation among participants to maintain coordinated action. It considers the mutual knowledge, beliefs, and assumptions among collaborating individuals. The CG concept has seen application in artificial intelligence agents [18], joint robot activity [19], and computer-supported cooperative work [20].

According to Clark, p is CG for members of group $\mathcal{G}$ if and only if [9]:

(1) Members of $\mathcal{G}$ know that p;
(2) Members of $\mathcal{G}$ know that members of $\mathcal{G}$ know that p;
(3) Members of $\mathcal{G}$ know that members of $\mathcal{G}$ know that members of $\mathcal{G}$ know that p.

Suppose that A and B walk in an airport terminal. As they pass a schedule board, A thinks that they should check the departure flight information and informs B of her plan to go to the board and to return to their current location, x. We denote the plan to divide-and-reunite at x as $\mathcal{P}$. For the plan to succeed, A needs to know that B knows the plan $\mathcal{P}$, and vice versa. This, however, is insufficient for coordination. B needs to know that A knows that he is privy to $\mathcal{P}$, otherwise he might not be convinced that A will return to x. Furthermore, if the agreement ends here, A may not know that B knows that she knows the plan, and may, therefore not be confident to execute the plan. Hence, A needs to know that B knows that she knows the plan.

The CG may be arrived at verbally, or may be enacted through action. For example, A may signal her intention by pointing toward the schedule board and pointing to their current location x. This requires that B be within the range of sight and be looking at A. A needs to see that B is looking at her and has signaled agreement (e.g., by nodding). B needs to see that A sees his nodding. Finally, A needs to see that B sees that she has seen and acknowledged the plan.

3. MULTI-AGENT SYSTEM

We operationalize our CGCS model for multi-agent systems using agent-based modeling approach. Agents are capable of perceiving and responding to their immediate surroundings and are organized into groups or 'co-travelers'. Group members maintain group cohesiveness by communicating and adapting their behaviors to each other. In the course of interaction, an agent may present gestures or other behavioral cues according to its communicative purpose. To accomplish this, our model maintains the communicative purpose of agents consistently from simulation through animations. We believe that this will produce more realism both in the overall simulation and individual animations of the agents.

3.1. Group Model

Our model assumes that the group memberships and eventual goal of groups are known in advance and not subject to change throughout the simulation. Members of groups are collocated at start and have the same final goal location. Goals are specific and definable geographic points in a given virtual environment. A global path that is used for collision-free navigation around static obstacles toward a final goal is precomputed for each group. The set of all members of group k is denoted G_k. We handle individuals in our simulation by permitting groups with a single member.

3.2. Agent Model

An agent with its personal identifier i is denoted as A_i. At the initial status of simulation, a group membership

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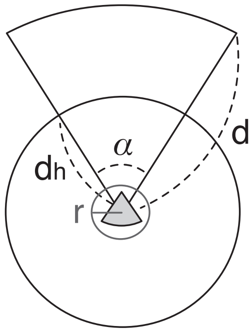


Figure 1. Agent perception geometry.

is assigned to each agent. A group may deviate from an original travel plan with goal interrupts to members of the group. For example, a member of a group may be triggered to visit the restroom (stochastically generated sub-goal) or to check a nearby schedule board for the flight information in an airport scenario (sub-goal generated through interaction with the environment), then the agent proposes a plan to satisfy the sub-goal to the group. As an available environmentally driven goal, each agent maintains a list of interests $I_{i,\tau}$, $\tau = 1, \ldots, K$ and corresponding propensity-to-visit values ranging from 0 to 1.0. When encountering some points of interest, an agent compares its propensity-to-visit value with the attraction intensity of the place and selects potential sub-goals.

To interact with group members, an agent should be able to understand status and intentional signals of the members and adapt its behaviors. We model an agent as having sensory capabilities for speech, vision, and touch. Figure 1 shows an agent's sensory model with a perception geometry. Touch can be sensed within range of agent radius r, hearing is omnidirectional with range limitation d_h, and vision is directional and is effective up to a range, d_v, along its gaze direction (for simplicity, body orientation is synonymous to gaze direction in our simulation) and within a field of view defined by an angle, α.

4. MODEL OF SOCIAL GROUP BEHAVIORS

At each time step, a group travels toward a final goal by following a preplanned global path. A group walks in a clustered way by minimizing the distance between members while avoiding collisions to each other. When a sub-goal is triggered, the group evokes a set of coordination behaviors.

Figure 2 illustrates the behavior decomposition in our model into the following: (i) macro-coordination; (ii) micro-coordination; and (iii) atomic action units. Macro-coordination relates to the overall high-level activity determining the spatial movements of group members over time to accomplish a navigation goal and sub-goals of a group. The plan of divide-and-wait in the airport scenario in Section 2.2 is an example of a macro-coordination behavior. The micro-coordination plan simulates the negotiation of CG among group members to decide on a macro-coordination plan given a new sub-goal. A micro-coordination plan may be further decomposed into a set of 'purposive' action blocks of reciprocal actions among the groups (hence reciprocating action block, or RAB). RAB may specify that an agent needs to gain the attention of its group members, indicate the location of a sub-goal, or specify a meeting point for the group after the sub-goal is completed. Atomic actions are behavior pieces that may be animated and can be used to build the RAB or the actions needed to accomplish a macro-coordination plan.

4.1. Macro-coordination

When a sub-goal is triggered, a group may select a macro-coordination plan from a predefined set of possible plans. This set of plans are designed to satisfy the needs of particular simulation/animation requirements.

For instance, in an emergency scenario, a set of macro-behaviors may be to abandon an original goal and find the nearest exit, to follow an authority figure, or to find a missing member, and a military simulation may specify doctrine-specific coordination plans. The plan selection is based on a probabilistic preference function, and members of a group share the chosen macro-coordination plan by each doing their participatory actions in particular roles. The selection of a macro-coordination plan results in a set of values for heading direction, desired position, and velocity for those agents involved in a group activity.

Because our interest is on generating social interaction behaviors of agents in a pedestrian simulation, we provide four macro-coordination plans for the most common navigation strategies. The four macro-coordination plans are 'detour-together', 'divide-and-wait', 'divide-and-meet', and 'divide-and-proceed'.

If a 'detour-together' plan is selected, the entire group detours together when a group member has to go to some point of interest. This plan reflects the follow-the-leader behavior, which is a commonly adopted approach for simulating group behaviors in other work [14,21]. In the 'divide-and-wait' plan, an agent heads for a sub-goal by itself while the rest of a group members stay at the current location. After it achieves the sub-goal, the divided agent returns to where it left the group members. If different sub-goals are simultaneously generated for multiple agents, the 'divide-and-meet' behavior allows for all agents or sub-groups to go and execute their sub-goals and return to the point of separation. This plan can be thought as analogous to a temporary sub-group generation observed in real group movements [3]. Once all parties have accomplished their sub-goals, they return to the previous location where they divided up and resume the original navigation when the group is reconstituted. If the 'divide-and-proceed' plan is selected, a member that received the sub-goal trigger

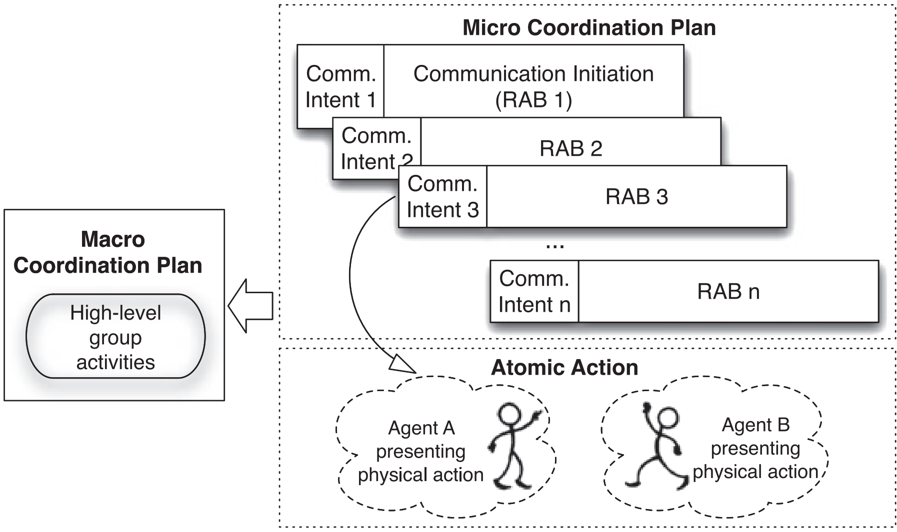


Figure 2. Behaviors decomposition in the common ground based crowd simulation model.

detours to visit a sub-goal while the rest of members proceeds with their original navigation plan. They reunite at the final goal location.

4.2. Micro-coordination

In our model, micro-coordination relates to the simulation of CG negotiation. We call this a micro-coordination because it is always situated and local to the current group configuration. Figure 2 shows how a plan is composed of a set of RABs involving group members to simulate CG negotiation.

4.2.1. Reciprocating Action Block.

Reciprocating action blocks consists of a set of actions to simulate the execution of a specific unit of communicative intent (e.g., an agent getting the attention of its interlocutors). An action block typically involves dual actions that need to be executed together or consecutively (e.g., the interlocutor nods when the first agent waves in its field of view). The utility of the block is thus to create cohesive atomic behaviors within a coordination sequence. Table 1 illustrates such an action block in our airport scenario. A may signal her intention $\mathcal{S}$ of heading to a schedule board by pointing toward it. This is followed by B signaling acknowledgement by nodding at A.

Table 1. Reciprocating action block.

Role	Action description
Proponent	A presents s_a to B intending that $\mathcal{S}$
Respondent	B takes up s_a by presenting s_b

Initially, an agent who receives a sub-goal trigger is assigned with a proponent role. As the communication proceeds, the roles may be interchanged. For example, at the proposal of using the 'divide-and-stay' macro plan from A, B understands the intention of A but may suggest to use the 'divide-and-meet' plan by pointing where he wants to drop by. Then, in the next chunk of RAB, B takes a proponent role and A becomes a respondent.

4.2.2. Communication Initiation.

The first RAB in a micro-coordination plan is always the preparatory action needed to ensure effective communication. For an agent who needs to initiate communication, it must first identify the other member agent and the spatial relation between them.

The agent has to assess the state of the respondent agents with respect to their perception model described in Figure 1 and perform a necessary action to meet the condition for establishing communication.

Figure 3 illustrates possible spatial relations of any two agents, A and B. In this case, A is the initiator of an

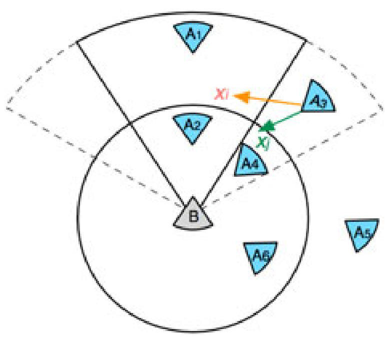


Figure 3. Six possible spatial relations of group members.

interactive exchange. Hence, A has to evaluate the state of perception of B depending on where she is with respect to B. There are six possible spatial relations, labeled $A_1 \ldots A_6$ in the figure. If A determines it is in the A_3 position, it is outside the immediate perception of B and has to move into a position where one of her means of communication is possible. A micro-coordination action may then be selected to move within B's field of view (e.g., position x_i). The second action block is for A to get B's attention (e.g., by waving). An alternative action block may be to have A walk into hearing range (e.g., position x_j), before calling out to B to get his attention. If more than one action block is available to satisfy the condition of the communication initiation, one is picked randomly.

4.2.3. Chains of Coordination.

An example of micro-coordination plan composed of a set of RABs between two agents is shown in Table 2 (note that a micro-coordination plan may be extended to include any number of participants). A moves to be within B's range of view to initiate communication. In the following RAB2, A may wave at B to get his attention, and B gives attention to A by turning at A. Next, in RAB3, A may point to the schedule board for indicating that she wants to check the departure time, and B looks at where she points as a response to her signal. However, B wants to go to a restroom, so he points towards a nearby restroom and then to their current location. A understands what he means, so nods at him, in the RAB4 stage. As B sees A's nodding at him, B nods back to her to indicate that he knows that she got the plan. A finalizes that they are on the same plan, and both take the movements.

4.3. Atomic Action

Reciprocating action block specifies the reciprocating atomic actions that satisfies a particular communicative intent. More than one RAB may satisfy an communicative intent, and the selection of RABs can provide behavioral variability, leading to greater believability. We show examples of the high-level communication intents and corresponding RABs (as atomic action pairs) in Table 3.

Table 2. Micro-coordinations plan, μ_β.

Step	Action Description
RAB1	*A* moves to be within *B*'s view range
RAB2-1	*A* performs a *signaling action*, s_a
RAB2-2	*B* gives attention to *A*
RAB3-1	*A* proposes a macro plan, $\mathcal{P}_\gamma$ (i.e., select $\mathcal{P}_\gamma$)
RAB3-2	*B* signals his understanding of *A*'s intention
RAB4-1	*B* proposes a macro plan, $\mathcal{P}_\delta$ (i.e., select $\mathcal{P}_\delta$)
RAB4-2	*A* signifies acknowledgement for $\mathcal{P}_\delta$
RAB5-1	*B* accepts *A*'s acknowledgement
RAB5-2	*A* finalizes the agreement on using $\mathcal{P}_\delta$
	If μ_β is successful, return TRUE (i.e., execute $\mathcal{P}_\beta$), else Return FALSE (coordination failed)

5. PERCEPTUAL STUDY AND RESULTS

Our CGCS model derives from CG theory with a basis in extensive observational science and provides a means to simulate purposive behavior of human groups in interacting. The open research questions are whether this model is suitable for crowd simulation, and whether our operationalization of the theory produces realistic crowd models. The question may be reformulated by asking whether our model produces plausible animations from the viewpoint of human observers in a series of user studies.

Because our model decomposes the overall coordinated behavior of groups into Macro-coordination and μicro-coordination components, we designed a set of pairwise-comparative studies to investigate the efficacy of the approach. In this section, we shall discuss the virtual setting in which our tests are conducted, the study conditions tested, the design of the studies, and our study results.

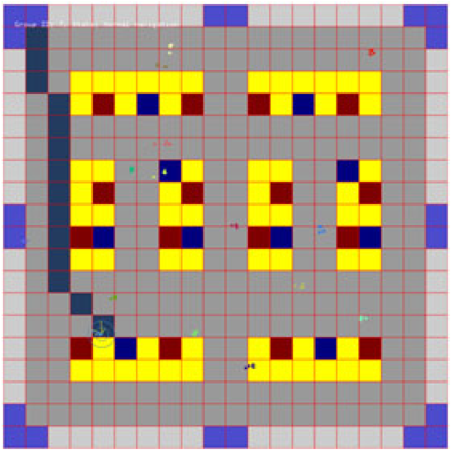
5.1. Virtual Environment and Scenario

In our studies, the simulation takes place in a virtual airport setting. 2D and 3D representations of our airport model are shown in Figure 4. The airport terminal contains 10 restrooms (dark blue squares), 16 flight schedule boards (red squares), and 62 stores (yellow squares) as potential sub-goals. Eight gates (light purple squares) are generated as possible final goals for agents. A* algorithm is used to generate a global path for each G_k. An initial navigation plan of G_7 is drawn in navy blue on top of the 2D map of the airport in Figure 4(a).

A crowd in each animation was made up of 60 individuals, 104 groups of 2 individuals, 30 groups of 3, 6 groups of 4, thus 200 groups in total. This distribution of pedestrian was determined by approximately following the information reported in [2]. However, to make the gestures of characters easily observable to viewers, the camera

Table 3. Examples of communication intents and corresponding micro-behaviors.

Communication intent	Reciprocating action block selected
Initiate communication	*A* moves into *B*'s view; *B* turns toward *A*
Request attention	*A* waves in direction of *B*; *B* looks at *A* & nods
Suggest macro-behavior	*A* points toward sub-goal; *B* nods at *A*



(a) 2D map

(a) 3D animated scene

Figure 4. Airport terminal model.

was set to focus at a few number of groups, but not at the overall scene.

For all of the individuals and agents of groups, one of the eight gates is selected as a final goal at random. Starting from initial positions, agents walk around the terminal and eventually proceed to the gate. A random event generator may trigger agents to visit the nearest restroom. When agents pass by schedule boards and shops, they may be attracted to some of the places. RVO2 Library [22] was used to generate low-level collision-free steering decisions.

5.2. Simulation Condition

To test the degree of realism afforded by our model, we generated a number of 30-second animations in the four conditions summarized in Table 4. We varied whether μ-coordination was included in the simulation, and the kind of M-coordination strategies employed. When no μ-coordination is used, the groups just proceeded to the M-coordination plan once a sub-goal is introduced. In CDT and CμDT, the groups always chose commonly used detour-together strategy [14,21], and in the CM and CμM condition, our four Macro-coordination plans described in Section 4.1 were employed.

5.3. Study Design

We tested our study conditions using a pairwise comparison design. To determine the effect of micro-coordination on human perceptions of the crowd behaviors produced by our model, we compare CDT versus CμDT with CM versus CμM. The first comparison tests the effectiveness of introducing CG to the common detour-together strategy [14,21], and the second comparison tests the effectiveness of adding CG to a more varied set of macro-coordination strategies. We use two measures as our dependent variable. The first, $\mathcal{M}_R$, measures the participant's estimation of the realism of a simulation, and the second $\mathcal{M}_P$ measures the participant's estimation of the plausibility of a simulation.

Table 4. Study conditions.

Condition	μ-Coordination	M-Coordination
CDT	No	Detour-Together
CμDT	Yes	Detour-Together
CM	No	Varied
CμM	Yes	Varied

For each pair of model comparisons, the participant were shown several animation pairs that were generated using the two models. That is, each participant was shown 10 pairs of different CDT and CμDT, and 11 pairs of different CM and CμM animations. The order of the presentations were randomized. We followed a within-subjects design, therefore all of the participants were shown the 21 pairs of animations.

Our study consists with three tasks. The first two tasks are for the realism and plausibility measures. The third task is for investigating participants' understanding of character behaviors.

For our realism measure, we employ a cover story to avoid demand characteristic biases. For each pair of simulations presented, the participant was told that one animation was derived from tracking data from a real crowd, and the other was synthetically generated. The participant was given a forced choice task of determining which was 'real' and which was synthetic. $\mathcal{M}_R$ measures the realism estimate for a simulation condition as the fraction of the number of times a simulation in that condition is rated as 'real' across multiple exposures. For example, if a participant judges 7 of the 10 CμM simulations as being from 'real data', then CμM has a $\mathcal{M}_R$ score of 0.7 (and CM has a $\mathcal{M}_R$ score of 0.3).

For our plausibility measure, participants were asked to say if the behaviors of the groups in a particular simulation are plausible on a 7-point Likert scale. Hence for our 10 presentations, each simulation model will have 10 Likert scores. The plausibility measure $\mathcal{M}_P$ of the model is the average of the 10 Likert scores.

To obtain a better understanding of the criteria used by our participants to judge plausibility, an additional pair of CM and CμM simulations were shown to the participants where three members of a group select the 'divide-and-stay' plan. This time, we highlighted a particular group of agents in each simulation (with a white circle). Participants were asked to describe their impression and understanding of character behaviors in the animations they saw. The rationale for this third study condition is the notion of 'narrative intelligence' whereby one's belief concerning the truth of a phenomenon is dependent on one's ability to explain the phenomenon [10,23]. At the end of our three-part study, the participants were given a semi-structured interview to gain better insight for how they judged the realism and plausibility of the simulations.

Figure 5 shows some animation scenes from the pair of CM and CμM, which was used for this task. Characters start from the same initial positions (Figure 5(a)) and the focused groups select the divide-and-stay plan (Figure 5(c)). Before a split occurs, the characters exchange communicative actions in the CμM condition (bottom of Figure 5(b)) while they simply leave each other in the CM condition (top of Figure 5(b)).

5.4. Procedure

Forty-two volunteers (28 women, 14 men), aged 18 to 38, were recruited for the study. At the beginning of the study, we showed them a demo video of our virtual airport terminal with a large number of virtual characters.

5.5. Results and Discussion

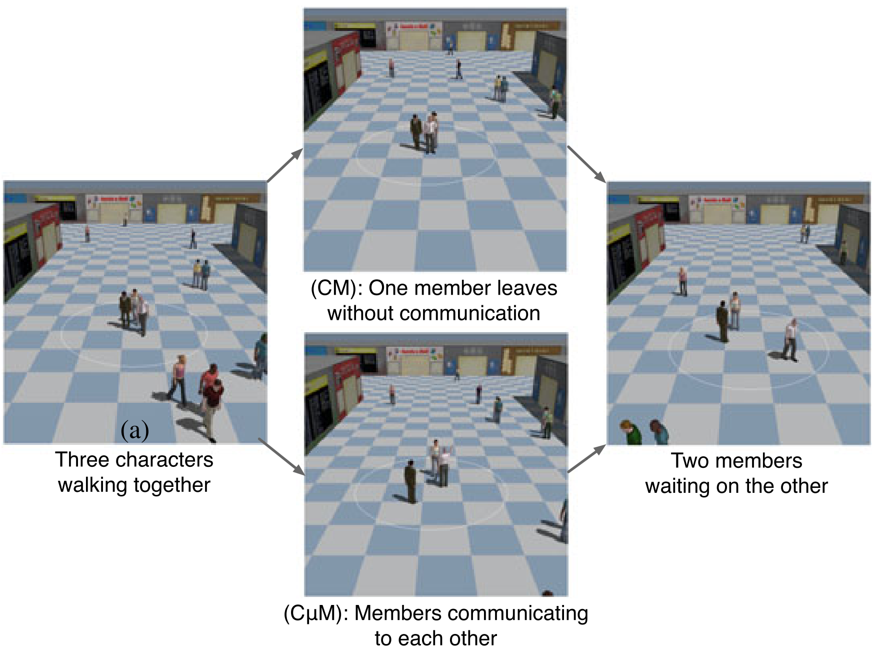
5.5.1. Quantitative Analysis.

We hypothesized that groups employing μ-coordination would appear more realistic and believable than the groups without the μ-coordination. Specifically, we hypothesized that groups in CμDT and CμM simulations would score higher $\mathcal{M}_R$ and $\mathcal{M}_P$ than those in CDT and CM simulations, respectively. Paired t-tests were conducted to compare $\mathcal{M}_R$ values for CDT and CμDT with CM and CμM animations, and $\mathcal{M}_P$ values for CDT and CμDT with CM and CμM animations.

We found a significant effect of incorporating social behaviors of coordination in the participants' responses on the crowd animations. Figures 6(a) and (b) show that participants chose the CμDT groups as real more often than the CDT groups ($p < 0.01$), and CμDT groups as more plausible than the CDT groups ($p < 0.01$). The analysis results in Figures 7(a) and (b) also confirm that participants rated the CμM groups as real more often than the CM groups ($p < 0.01$), and CμM groups as more plausible than the CM groups ($p < 0.01$).

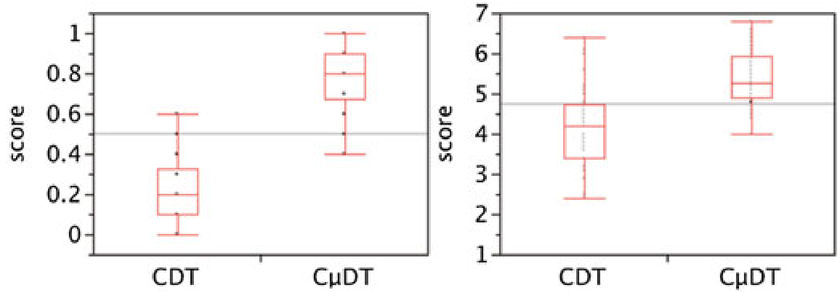
5.5.2. Qualitative Analysis.

We employed two qualitative approaches to analyze our qualitative data. First, we analyzed the participants' responses for objective statements of belief concerning



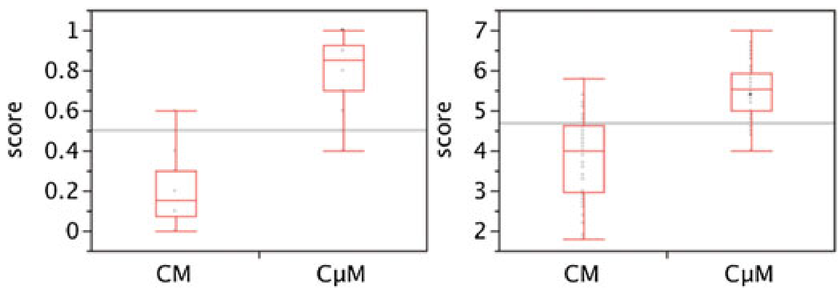
(a) (b) (c)

Figure 5. A paired CM and CμM animations.



(a) $\mathcal{M}_{\mathcal{R}}$ (b) $\mathcal{M}_{\mathcal{P}}$

Figure 6. CDT versus CμDT.



(a) $\mathcal{M}_{\mathcal{R}}$ (b) $\mathcal{M}_{\mathcal{P}}$

Figure 7. CM versus CμM.

each model in the third task. This allows us to determine why one model was judged as more believable than another. For the CM animation, 10 participants stated that they were not sure on what was going on in the animation (e.g., "it seems strange, the people randomly stop and one person leaves"). Twenty-four participants provided just a factual description of what they witnessed without providing any reasons for what they saw, for example, "one guy in a suit walked away while others are standing." Ten among these 34 indicated that they thought the characters are not with together (e.g., "I think the first two are traveling together, and the guy at the end wasn't with them"). Eight subjects made an interpretation in which they assumed the group members communicated before they split up.

In contrast, for the CμM animation, 40 subjects indicated that they had a better understanding of the character behaviors, and interpreted the split as resulting from negotiation (e.g., "one of the character actually told the other two characters to wait on him"). Ten of the 40 subjects explicitly stated that the CμM animation was much more clear, and it was because of the exhibition of communicative acts of characters (e.g., "there was obvious communication between the members of the group so it was very direct and I didn't have to assume what was going on"), and 11 of them added more stories into their description (e.g., "he might say something like 'do you know where we have to go,' so he checks..."). Two provided the similar factual description to what they had for the CM animation.

In the semi-structured post interview, we asked participants what criteria they used to evaluate animations. To obtain categories for the rationale for the participants' beliefs, we employed an open coding method [24]. We performed two passes through the data. In the first pass, we collected categories of responses concerning belief, and in the second, we employed these categories to group the participants' responses.

Through our analysis, we were able to determine three categories for reasons that the participants rated the CG model as more believable. The three categories of rationale are *interaction*, *formation*, and *cohesion*. In the interaction category, participants were attentive to whether there was evidence of interaction among characters before stopping or changing direction while walking (e.g., exchange of gestures, body alignments to talk). Subjects answered that the characters with the μ-coordination behaved in a way that allows them to structure the sequence of behaviors into a narrative whole and makes the animation be more comprehensible and believable. For the formation category, spatial patterns of groups such as side-by-side walking and linear walking formation were considered. In the cohesion category, subjects looked for whether group members maintained appropriate proximity and/or respected group integrity (i.e., circumnavigated other groups rather than just cutting through them). As shown in Figure 8, 34 participants employed interaction, 5 used formation, and 3 used cohesion as their criteria to make their evaluations.

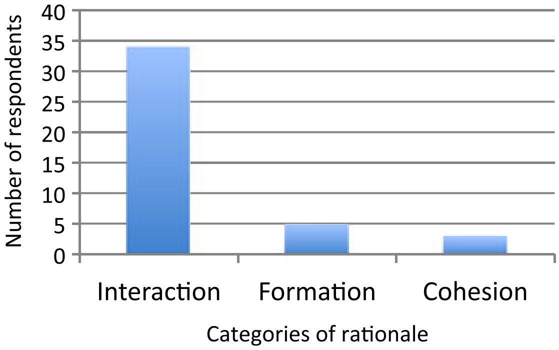


Figure 8. Criteria used to evaluate animations.

Our results demonstrate that the believability of an animation is affected by communicative and social interactions among characters. People are attentive to not only what the characters do but also why, because they try to understand the chains of character behaviors by constructing a coherent story [10]. People rated a given animation realistic and more plausible when they thought a specific walking strategy (e.g., divide-and-stay) of a group was made as a result of communication among the characters. This indicates that the meaning of behaviors of individuals in group activities is not decidable in isolation, but people relate the behavior to the behavior of interacting entities to understand them. It is shown that the comprehensibility may be essential to believable agents, and this suggests that the model of character behaviors should be designed to provide interpretability, or rationality, to external observers for achieving the enhanced realism.

6. CONCLUSION

In this paper, we presented a model of social group behaviors using Clark's CG theory to accommodate high-level sociality of characters in a crowd simulation. The CGCS model enabled our agents to present communicative behavioral cues in coordination with other agents in a group. We conducted a user study in which the efficacy of our CGCS model was examined. The study results showed that the communicative purpose in our model can be consistently carried through from simulation to animation, and it produces more believable behaviors of animated characters from the viewpoint of human observers.

Our future research direction includes extending our model to handle sub-groups and various types of relationships. In the real world, individuals are embedded in different social structures simultaneously, such as sub-groups (e.g., parents, siblings), groups (e.g., family), and organization (e.g., pedestrians). Also, intergroup ties could vary (e.g., pedestrians–pedestrians, pedestrians–authority figures). The different social relationships may have an impact on the use of micro-coordination and macro-coordination strategies. For example, pedestrian–pedestrian coordination will require the construction of ad hoc proximal groups with different strategies. Such extension will provide interesting challenges to extensions of our model.

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